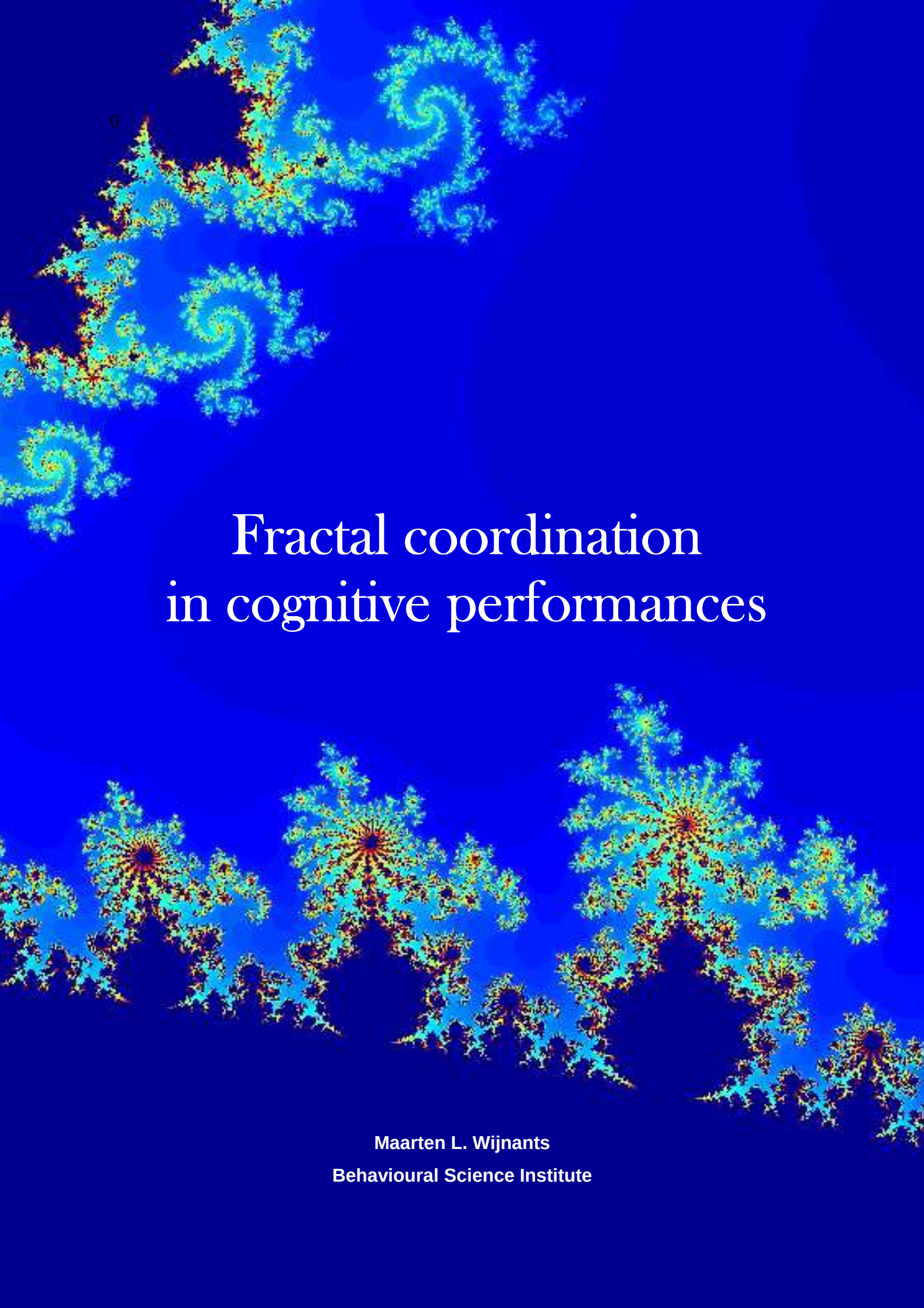

Fractal coordination in cognitive performances

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To the memory of Guy

who will always be with us

in our hearts, minds and bodies

Fractal coordination in cognitive performances

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Chapter 1

General introduction

CHAPTER 1

"The ideas were simply too far ahead of their time; it was enough of a jump to go from stimulus-response theory to notions of a flow of information through the nervous system, without complicating the matter by different levels and spans of time" (Broadbent, 1977, p. 184).

One of the most challenging aspects of human behavior is to understand how people coordinate their everyday actions, because the answer must go beyond isolated processes grounded in perception, memory, attention, language processing, problem solving, emotion, or motor control. Human coordination rather pertains to cooperative sets of cognitive functions. The question of how coordination in human behavior emerges thus hinges on the way in which cognitive functions mutually co-exist and interact in order to serve stable yet flexible behavior.

Historically, response durations have been the most prominent workhorse for behavioral scientists to unravel coordinated cognitive activities, and the present studies are no exception. Conventionally, response durations are expected to inform about processes that start off whenever a given stimulus is being perceived, and end up with a response. Every time a stimulus is presented, the selfsame 'sense-compute-act' process is supposed to start over. In repeated performances, each response process is thus assumed identical to the next, yielding approximately the same duration on average, plus a given degree of random variability.

The fact that relevant cognitive activities are assumed to operate within the time frame between stimulus presentation and response stems from a deeper theoretical belief. That is, cognitive activities are generally viewed as arising from the sum of component effects, where each component serves a functional sub-process and spans a sub-interval of response duration. The idea of modular minds traces back to Descartes' reductionism, and still governs contemporary thinking about intelligent systems. Although the non-physical mind was abandoned when dualism was eventually rejected in psychology, the basic shape of the architecture remained. After the cognitive revolution, the non-physical mind was replaced with a mechanistic concept of cognition. Modularity of mind, also referred to as Computational-Representational Understanding of Mind (CRUM), can be considered the current dominant approach in cognitive science (cf. Thagard, 2005).

Motivated by the computer metaphor, CRUM conceives the cognitive system as an input-output device, which operates through discrete, functional system components and processing stages. Perception is the input (stimulus), action is the output (response), and all the things in-between are specialized information processing devices. The workings of the internal components are based on rules, algorithms, or procedures (mental grammar or computations) operating on symbolic mental representations (mental vocabulary or 'neural code'). The underlying idea is that the mind and brain are collections of specialized devices, and that measured behavior can thus be partitioned among these devices (e.g., Pachella, 1974; Sternberg, 1969).

This theoretical framework has a profound impact on the use of statistical methods as well. As a historical example, Donders' subtraction method (1868) attempts to identify stages of information processing, by subtracting response times of a task with an additional requirement from response times of the same task without that requirement, in order to estimate the duration of the manipulated cognitive process. Although the historic subtraction logic had a number of known pitfalls, the subtraction idea still forms the basis of much modern functional brain imaging and computational modeling work. That is, the standard

strategy for making progress in cognitive psychology consists of breaking down complex problems into smaller sets of (hopefully) simpler sub-problems, so that the original problem can be solved by combining the solutions to each sub-problem.

Certainly, divide-and-conquer has obvious strengths, such as making analytic understanding and formalization easier because of the ability to isolate processes. Nonetheless, the initial excitement that emerged from information-processing theory in the fifties of the 20th century was followed by a succession of failures to agree on both the location and function of the components that spans the history of behavioral science (Uttal, 2001; Van Orden, Pennington, & Stone, 2001). It is unclear, therefore, whether cognitive activities are in fact understood in enough detail to warrant that they can be taken apart as component causes. And even if we would eventually understand how a brain in a body implements many individual processes, it does not follow that we understand how these processes interact in a coordinated manner. Thus, understanding human behavior justifies the hypothesis that cognitive activities do not just reside within specific components but rather in the coordination among the components.

Interaction dominance

The hypothesis that the intrinsic dynamics of the components matter less than the mutual interactions among components is called *interaction dominance*. This position is antithetical to the more traditional *component dominance* discussed above, in which the intrinsic activities of the components are held to be much more influential and dominant in determining observed performance. Interaction dominance shifts the focus from studying the sub-parts individually, to studying global phenomena that are the irreducible result of local interactions between the components. Such global phenomena are often referred to as emergent phenomena, because it concerns features that are not implicit in the parts of the system.

Emergent properties of complex systems reveal themselves as unexpected orderly spatio-temporal patterns in the behavior of the system. Consider for instance an example as simple as a pan of water that is put on a hot surface. When the large collection of H_2O molecules is heated evenly from below but cools down evenly at its surface, the heated molecules move upwards towards the surface and the cooler molecules at the surface sink to the bottom, because warm liquid is lighter than cold liquid. As the difference in heat between top and bottom increases, the two opposite movements can no longer take place at the same time without some kind of coordination between the two flows of liquid (i.e., an upward flow for warmer molecules, and a downward flow for colder molecules). At that critical point, the liquid tends to self-organize into an emergent pattern of parallel rolls, with an upward flow on one side of each roll and a downward flow on the other side, meaning that the molecules in the liquid that were moving in random directions at first end up all moving in a coordinated way that optimally dissipates the heat.

This example shows that when all components in a system are directly or indirectly connected, the components change each other's dynamics as they interact, changes that propagate throughout the entire system. The system organizes itself by itself in the sense that the interactions among the molecules greatly reduce the collective degrees of freedom of the system and thereby spontaneously coordinate the behavior of the selfsame molecules. In this way, the whole pattern of rolls in the pan emerges spontaneously (i.e., in the absence of an external controller) from the collective properties of the molecules in the fluid and the geometry of the pan, and cannot be predicted from the properties of the parts alone.

Metaphors like the example above can be helpful in illustrating how interaction dominance allows coordination to be an emergent property. In systems consisting of a large conglomerate of interacting components, local interactions embedded in larger scales of feedback can spontaneously organize themselves as functional dynamic patterns, without requiring the functional subdivision among the components that is typically assumed. Secondly, the metaphor illustrates that the dynamics of the system are the entry level at which emergent properties can be revealed and quantified. Interaction dominance together with some simpler and some more advanced time-series analyses, allows emergent phenomena in cognitive activities to be studied. That is, time series of response durations can be investigated to better understand the emergence of coordinated behavior.

$1/f^{\alpha}$ noise

The majority of efforts in cognitive psychology rely on statistical tests that depend on the average duration of response processes, and the magnitude of variability around that mean value. And as I explained before, the interest in average response durations is based on the assumption that the mechanisms of interest operate in the timeframe between the presentation of a stimulus and a response. Variability around the mean is generally considered as random error and assessed in terms of magnitude through the calculation of variance, standard deviation, or coefficient of variation. Hence, changes in performance over time are considered unstructured, and therefore, uninteresting. What this means in practice is that data deriving from a single participant is generally not kept intact as a response history, but is diced up among treatment cells that express the design.

Over the last decades, however, it has become clear that looking at changes in performance over time provides more information about the underlying system than would ordinarily be expected. This has led to an increasing interest in the measure-to-measure fluctuations of cognitive activities, because the assumption of random variability is simply not in accordance with actual data. That is, random response-to-response variability is the exception rather than the rule in a time series of repeated performances (Gilden, 2001; Riley & Turvey, 2002; Slifkin & Newell, 1998; Van Orden, Holden, & Turvey, 2003). This means that a time series of repeated performances usually reveal a rich dynamical structure when the data values are kept in the original order of measurement.

Consider for instance the example sequence of response durations shown in Figure 1. It can be seen that the data series is composed of many high-frequency and low-amplitude fluctuations nested within low-frequency and high-amplitude fluctuations. In other words, changes that occur often are small, and embedded in much slower but larger changes. This unexpectedly orderly nested pattern markedly deviates from random noise, and is called $1/f^{\alpha}$ scaling, where α corresponds to the negative slope in the log-log power spectrum (shown in the lower right panel of Figure 1). For ideal $1/f$ scaling, the scaling exponent α equals 1 since power and frequency are inversely related on log-log scales. The $1/f$ scaling pattern is not transient (i.e., does not dependent on a few immediately preceding responses) but persists over the whole “history” or ‘memory” of the series, and is often considered a universal statistical property that emerges from the behavior of complex systems.

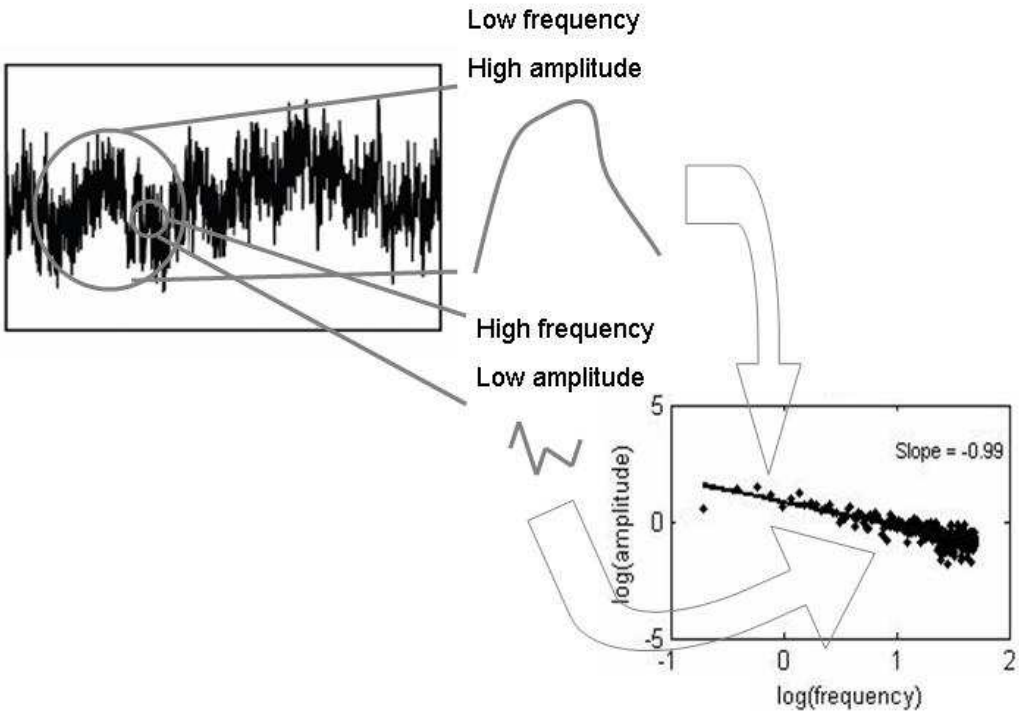

Figure 1. A time series revealing approximate 1/*f* scaling is shown at the left. Its decomposition into composite frequency components is shown in a power spectrum at the right.

1/*f* scaling is a special type of variability because it constitutes a fractal process. Fractal processes reveal the distinct property of self-similarity across many nested scales. That is, rescaling the time axis does not change the statistical properties of the series because structure at the large scale is statistically indistinguishable from structure at a small scale (see Figure 2). This means that emergent fractal patterns in a data series indicate the presence of system dynamics that extend beyond the time boundaries of single trials or events, and evolve across multiple interdependent timescales of performance. Thus, the widespread presence of 1/*f* scaling in human performance suggests that cognitive activities hinge on evolvements over a much wider range of timescales (i.e., up to minutes of performance and more) than the characteristic scale on which cognitive activities are typically studied (i.e., roughly 200 to 800 ms).

If a response series would truly show random variability, response durations would not be correlated over time as in 1/*f* scaling. One way to get random noise is by shuffling the original data series, which would make the time-dependent pattern of change disappear. As shown in Figure 3, random variability can be described as $1/f^0$ noise. Observing random noise would justify studying response processes at a measurement scale that spans an interval between the presentation of a stimulus and a response, simply because processes that evolve over longer timescales are absent, and therefore irrelevant.

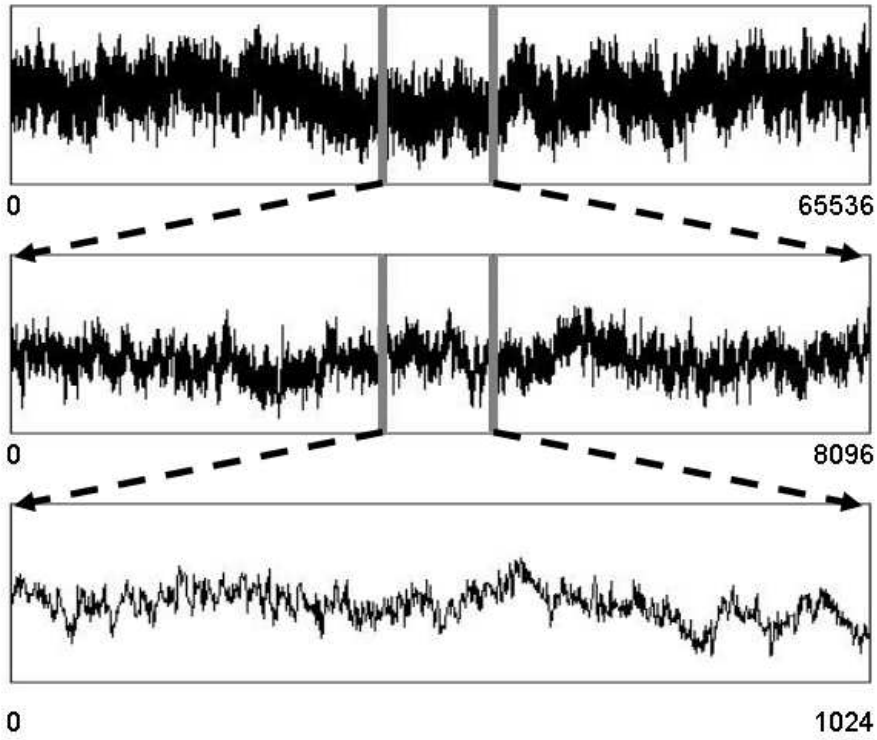

Figure 2. Statistical self-similarity in a data series of repeated measurements: smaller parts of the process are similar to larger parts.

The difference between 1/*f* scaling and random variability is not an all-or-none difference, however. Actual performances usually fall somewhere on a continuum between random variability and self-similar 1/*f* scaling, and thus yield a scaling exponent α that varies between 0 and 1. Examples of cognitive tasks include mental rotation, lexical decision, and visual search (Gilden, 2001), simple reaction time and word-naming (Van Orden et al., 2003), forearm oscillation (Delignières, Torre, & Lemoine, 2008), synchronization to a metronome (Chen, Ding, & Kelso, 1997), implicit associations (Correll, 2008), and bi-daily reports of self-esteem (Delignières, Fortes, & Ninot, 2004), among others.

The continuum extends beyond 1, however. For instance, a scaling exponent of 2 gives yet another class of noise, called Brownian motion. Brownian motion yields even higher amplitudes at the low frequencies (slow timescales of change) and even lower amplitudes at the high frequencies (fast timescales of change) compared with 1/*f* scaling, and can be described as $1/f^2$ noise (see Figure 4). This type of variability can be had by adding a random increment to the previous response (i.e., by integrating a random series), which results in a random walk. This type of variability is very persistent and rigid over time, and suggests a much less flexible system than would be suggested by 1/*f* scaling or random variability, because every other response is only a small persistent change from the previous response.

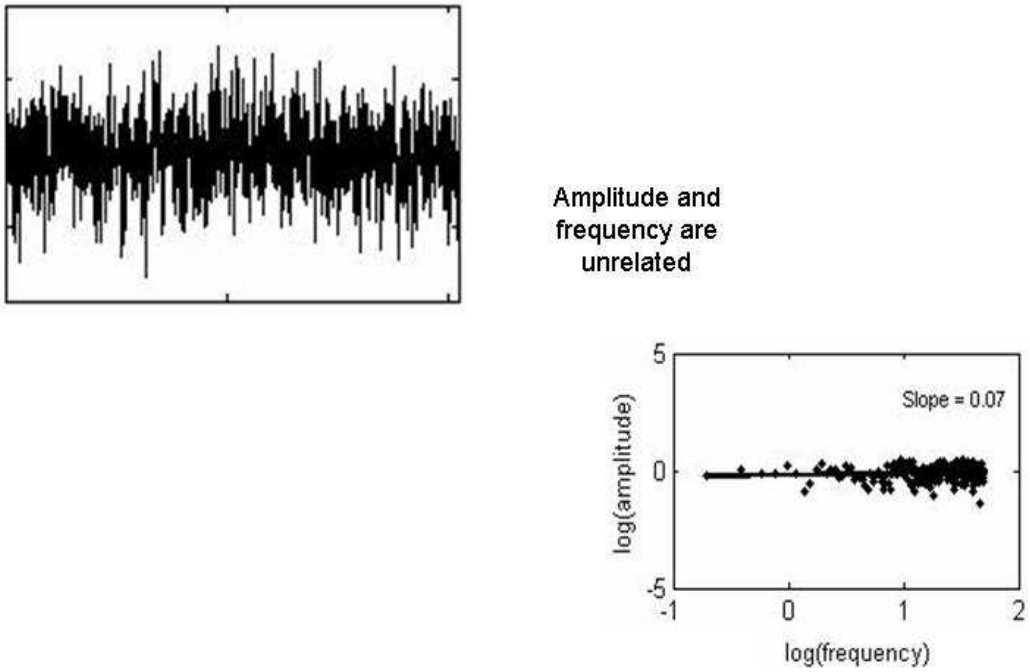

Figure 3. A time series revealing approximate random noise is shown at the left. Its decomposition into composite frequency components suggests independent measurements, as shown in a power spectrum at the right.

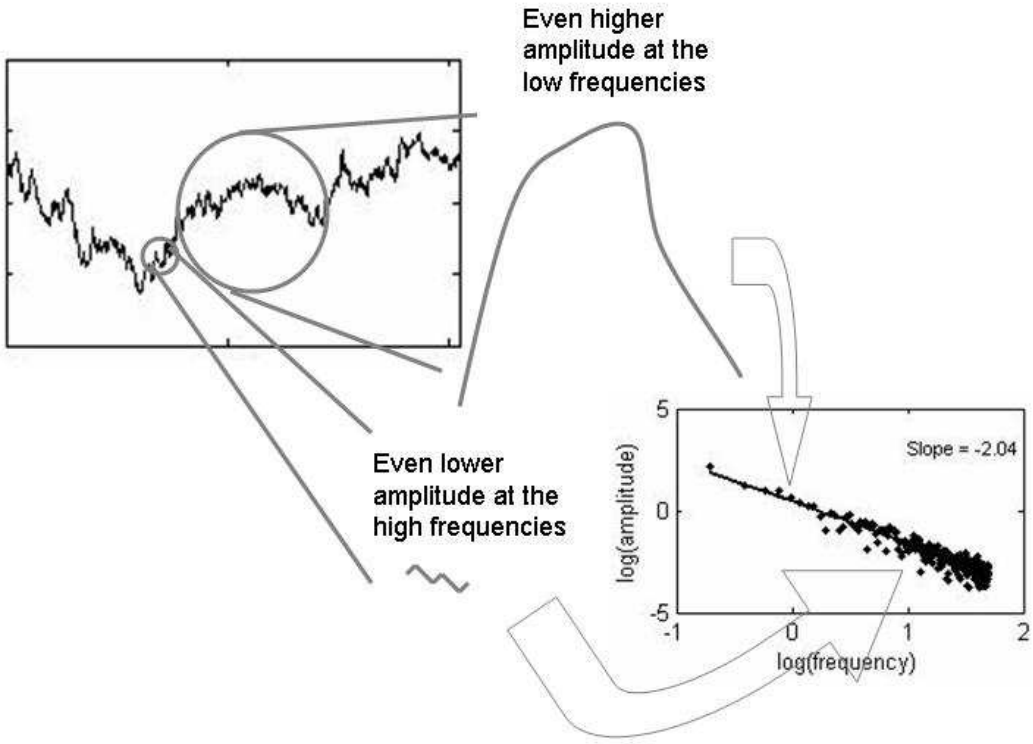

Figure 4. A time series revealing approximate Brownian motion is shown at the left. Its decomposition into composite frequency components at the right reveals that short-term changes in response are very small, but long-term changes in performance are persistently large.

Fractal coordination

There exist several well-established methods (e.g., power spectral analysis, detrended fluctuation analysis, standardized dispersion analysis, among others) to assess where on the continuum repeated performances live. Such an investigation of response durations allows investigating differences in the dynamical structure of experimental time series in different performances. For instance, some performances are closer to random variability, and are thus disordered and unstructured over time. Random variability allows for flexible and unconstrained performances, since each stimulus starts a new response process that is unlinked and unrelated to the previous response. Performances closer to Brownian motion, at the other hand, are overly persistent and rigid, suggesting highly constrained and inflexibly coupled components. Repeated performances that arise in a $1/f$ fashion fall exactly in between random noise and Brownian motion, and thus are precisely balanced at the frontier between disordered and persistent system dynamics. $1/f$ scaling thus neither suggests independent components, nor too rigidly coupled components, but rather a precise balance between overly flexible and overly inflexible system performance, which qualifies $1/f^{\alpha}$ scaling as a candidate metric for emergent coordination.

Its widespread presence in cognitive performances makes $1/f$ scaling an even more intriguing phenomenon and a hotly debated topic for well over a decade now. Why would cognitive activities at the edge of flexibility and rigidity appear exactly as $1/f$ scaling? One possible answer is provided by interaction dominance, which considers fractal $1/f$ scaling as a generic feature of the intrinsic fluctuations of complex systems, which indicates that the same processes are in play in the short and in the long run. Any measured behavior nests processes at faster time scales, and in turn, is nested within processes at slower time scales, and the behavior of any one process at any one time scale is susceptible to, and reflective of, the behaviors of all processes over many time scales. That is, from an interaction dominant perspective $1/f$ scaling in human cognition means that the many processes involved interact so completely, up to the periphery of the nervous system, that one can no longer parse out the individual activity of one component from another. Other, competing answers exist as well, however. That is, $1/f$ scaling is not strictly impossible from CRUM or any other component-dominant position. The widespread presence of $1/f$ scaling does pose a challenge to those ideas, nonetheless (i.e., motivating theoretically why there would be $1/f$). So, what could be the response of CRUM to the challenges imposed by widespread $1/f$ scaling in cognitive performances?

How to respond to the challenge?

Quite helpfully, Thagard (2005) describes four possible responses to the challenges imposed on CRUM. A usual first response is to simply *deny the challenge*. Examples in this vain taken from anonymous reviewers' comments include "Just because we have a series of response times does not mean that we have a time series, and does not necessarily lend itself to searching for $1/f$ noise", or "I can only conclude that the authors have simply presented us with some measures of performance over sequences of repeated movements that tell us nothing about the processes involved".

As Thagard explains, a second and admittedly more subtle approach is to expand CRUM by *adding new representational, computational ideas*. For instance, a reviewer may argue that, "There are certainly going to be changes from one trial to the next and over longer time scales due to feedback information being used for correction or adjustment of movement parameters

and through learning. There will also be fatigue effects". Another example was: "It is well known that short-term and long-term relations can be discovered in latency sequences, just by including lag factors in generalized linear analysis." Unfortunately, reviewers often forget to provide the theoretical and biological motivation for how and why their expanded version of the traditional model would account for the specific patterns of variation in the data.

A third way to go is supplementing CRUM by *adding non-representational/non-computational ideas*. For instance, it is possible to account for the presence of fractal fluctuations in series of performances by injecting emergent 1/*f* scaling in precise locations in classical models (e.g., Delignières et al., 2008; Diniz et al., 2011; Gilden, 2001). This approach has the advantage to respect fundamental aspects of previous theories that are accounted for by these classical models, while yet accounting for the new finding.

The last possibility is to *abandon CRUM*. This is the response one is likely to consider when accepting emergent coordination. Emergent coordination is strictly impossible in the standard componential 'sense-compute-act' model, and therefore motivates a more inclusive research program. That said, just observing 1/*f* scaling in some performance can neither be taken as a sufficient basis for emergent coordination, nor to reject CRUM. There are simply too many alternative explanations that are consistent with CRUM. To actually abandon CRUM is a) to reject that 1/*f* scaling comes from the summed activity of independent modules (i.e., solution 2), and b) to reject that 1/*f* scaling comes from a encapsulated module within the system (i.e., solution 3). In other words, abandoning CRUM means facing the uncomfortable insight that cognitive science and neuroscience have to deal conceptually, theoretically, and empirically, with complex systems that are much harder to grasp than simple, decomposable systems of quasi–independent modules.

To the extent that repeated measurements reveal 1/*f* scaling, cognitive psychology may find itself allied with modern theories of complexity where these types of temporal variability are even more actively being investigated (e.g., http://www.nslij-genetics.org/wli/1fnoise/). If cognitive activities are indeed the product of a complex system, this would mean that decompositional analysis is inherently destructive to what makes the system complex (i.e., its non-decomposable nature). From a complex systems perspective, there is no particular cognitive component that causes 1/*f* scaling. Instead, 1/*f* scaling is considered an emergent property that stems from the interactions across the many spatio-temporal scales of organization of an organism. From this perspective, it is opportune to look at cognitive performances just like one would look at physical processes in which multiple components become collectively coordinated through self-organization (e.g., convection rolls in a pan of boiling water).

Customary measures in psychology such as reaction times and errors, by themselves, simply fail to make contact with the full richness of cognitive dynamics and, as a result, underconstrain accounts of coordination. In this respect, the study of nonlinear dynamical patterns effectively enriches and extends the range of relevant observables in cognitive psychology. These metrics allow looking at emergent patterns in behavior, which potentially provides a more fruitful way of thinking about coordination. For instance, may human coordination simply reside from the coupled activity of processes that evolve over multiple interacting timescales? This question can easily be transformed into a testable hypothesis. That is, given that self-organization coordinates the processes of the body across their hierarchy of timescales, and that correlated activity across timescales produces 1/*f* scaling,

one would expect clearer 1/*f* scaling in coordinated cognitive activities compared with less coordinated activities. And that is exactly the hypothesis pursued in the present dissertation.

The chapters

In Chapter 2, motor learning was investigated in goal-directed pointing movements that were performed as fast and as accurately as possible. After 5 training blocks in a challenging task condition, participants were able to produce faster movements while maintaining accuracy. The study revealed that clearer 1/*f* scaling emerged in the movement time sequences with motor learning, an effect that was confirmed by a set of complementary dynamical measures (i.e., Recurrence Quantification Analysis and sample entropy). This study confirmed the hypothesized linkage between system dynamics and coordinated action and suggested that motor learning can be regarded as an increasingly dynamic fusing of collaborating subsystems into a lower-dimensional organization.

This finding has led to the study described in Chapter 3, which further explored reciprocal aiming movements by investigating the well-established speed-accuracy trade-off. It is known that in challenging task conditions, participants self-define their position along the continuum of speed versus accuracy while being equally instructed to move as fast and as accurately as possible. This study revealed clearer 1/*f* scaling in the preferred side of the trade-off, and less clear 1/*f* scaling in the competing side. That is, faster participants revealed clearer 1/*f* scaling in their movement time sequences, but more random variability in their movement amplitude series. Conversely, more accurate participants revealed clearer 1/*f* scaling in their movement amplitude sequences, and more random variability in the movement time series. The fractal dynamics were functionally related to the kinematic properties of the movements as well. The linkage between this finer measurement scale (i.e., pertaining to details within a single movement) to the more global measurement scale (i.e., over an entire sequence of movements) further suggested that cognitive performances are assembled over multiple, hierarchically embedded timescales.

These findings raised the question whether similar coordination principles could be observed in different cognitive domains. Chapter 4 therefore relies on a simple reading task, known as a word-naming task, which was presented to both average and dyslexic readers. As predicted, average readers revealed clearer 1/*f* scaling in their response times compared with dyslexic readers. In addition, strong correlations were found between the relative presence of 1/*f* scaling and the severity of the reading impairment. This study suggested that developmental dyslexia resides from dynamical instabilities in the coordination among the many components necessary to read, which could explain why dyslexic readers score below average on so many distinct tasks and modalities.

Chapter 5 constitutes a methodological contribution that improves the accuracy and reliability of estimating the relative presence of 1/*f* scaling in continuous processes. Bothered by an apparent inconsistency in the literature (i.e., continuous processes are often close to Brownian noise, whereas discrete processes are often close to 1/*f* scaling), an artifact is revealed that follows from blind application of fractal methods to continuous processes, and a simple and effective solution is offered.

The final part of the dissertation is devoted to the debates that have accompanied the study of 1/*f* scaling in cognitive performances. Chapter 6 contrasts the view of Delignières and colleagues with the perspective of interaction dominance. Chapter 7 offers a more general

discussion that confronts the most prominent positions in the debate on 1/*f* scaling in cognitive performances with the widespread linkage between clear 1/*f* scaling and well-coordinated behavior. Here, *widespread* means from the level of the cell up to the central nervous system and the rest of the body, to motor behavior and other cognitive performances. From this review, I conclude that interaction dominance is actually the least controversial and most parsimonious framework to account for these findings. Nonetheless, many challenges lay ahead…

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Chapter 2

1/*f* scaling in movement time changes with practice in precision-aiming

Based on:

Wijnants, M. L., Bosman, A. M. T., Hasselman, F., Cox, R. F. A., & Van Orden, G. (2009). 1/*f* scaling in movement time changes with practice in precision aiming. *Nonlinear Dynamics, Psychology, and Life Sciences, 13*, 75-94. Pubmed:19061546.

CHAPTER 2

Abstract
When people perform repeated goal-directed movements, consecutive movement durations inevitably vary over trials, in poor as well as in skilled performances. The well-established paradigm of precision-aiming is taken as a methodological framework here. Evidence is provided that movement variability in closed tasks is not a random phenomenon, but rather shows a coherent temporal structure, referred to as 1/*f* scaling. The scaling relation appears more clearly as participants become trained in a highly constrained motor task. Also Recurrence Quantification Analysis (RQA) and Sample Entropy (SampEn) as analytic tools show that variation of movement times becomes less random and more patterned with motor learning. This suggests that motor learning can be regarded as an emergent, dynamical fusing of collaborating subsystems into a lower-dimensional organization. These results support the idea that 1/*f* scaling is ubiquitous throughout the cognitive system, and suggest that it plays a fundamental role in the coordination of cognitive as well as motor function.

1. Introduction

Repeated instances of human performance are usually measured using summary statistics of central tendency and average variation around a central tendency. It can be more informative however to complement summary measures with time-evolutionary measurements (Riley & Turvey, 2002; Slifkin & Newell, 1999). Time series of measured values can be qualitatively different for identical means and standard deviations. For example, consider an artificial time series in which measured values follow an idealized sine wave across the trials of an experiment; measurements fluctuate around the mean in a deterministic, non-random cycle. Compare that with the same "sine wave" data rearranged in a random sequence of occurrence. The respective time series have equivalent means and standard deviations, but one comes from a random process and the other from a simple oscillating process.

Repeated measures of human performance oscillate in a more complex pattern than the sine wave, but it is a pattern nonetheless, and may prove just as revealing of underlying dynamics. Especially helpful in this regard are recent advances in the study of nonlinear dynamics. By applying an advanced nonlinear toolbox, it is possible to gauge fractal patterns in data, as well as indices of determinism or entropy and other descriptor variables (Riley, Balasubramaniam, & Turvey, 1999; Slifkin & Newell 1999). These tools are applied in the present case to test whether the pattern of variation changes with practice in a simple perception-action task. Our starting point is the observation of 1/*f* scaling in time series of human performance – the widely observed finding of long range correlations across successive data points in motor coordination experiments (Riley & Turvey, 2002; Slifkin & Newell, 1999; Treffner & Kelso, 1999) and cognitive performances (Gilden, Thornton, & Mallon, 1995; Gilden, 2001; Van Orden, Holden, & Turvey, 2003).

The widely observed 1/*f* scaling relation expresses aperiodic, fractal fluctuations of available frequencies across a time series of data. In a spectral decomposition of the data signal, however, the amplitude at a particular frequency of fluctuation is inversely proportional to the frequency itself. One observes a nonlinear, log-log relation between the frequency of variation across the data series and the magnitude of variation, for a given data set.

The pattern implies that no characteristic scales dominate the underlying process; the same dynamics occur at every scale, including very high amplitude and low frequency fluctuations. In fact, the more data one collects – that is the longer the data series – the larger the magnitude of variation for the whole set (Van Orden, Holden, & Turvey, 2005). Consequently the implicit amount of variance is undefined as total explicit variability increases rather than

stabilizes when larger samples are collected (Gilden, 2001; Holden, 2005; Mandelbrot, 1982). Interestingly, 1/*f* scaling appears to be a ubiquitous property of repeated measures in human performance (Kello, Beltz, Holden, & Van Orden, 2007). An example data series yielding a 1/*f* scaling pattern is presented in Figure 1a.

The phenomenon of 1/*f* scaling demonstrates the importance of considering how variability scales with sample size in behavioral data (Riley & Turvey, 2002). This information is not implied by the sampled amount of variability and can only be obtained by incorporating the dynamical properties of behavioral data as an essential aspect of measurement. Time series phenomena like 1/*f* scaling are simply unavailable in summary statistics such as central tendency or magnitude of variation. As in the example of the sine wave, 1/*f* scaling disappears if the original order of measurement is randomized.

Figure 1 illustrates this point using actual data. Figure 1b shows the same data series presented in Figure 1a after randomizing the sequence trial order in which the data points were collected. The same mean and standard deviation are computed from the randomized time series, but the time-evolutionary scaling relation is erased (compare spectra in Figure1c and Figure 1d). The rationale for summary statistics, however, the central limit theorem, specifies that collective aggregate properties of *independent* components obey a Gaussian distribution. Consequently, measured over a duration or sample size *T*, the standard deviation of a data series will increase as T^h where the exponent $h = ½$ implies randomness. For fractal processes like 1/*f* scaling, however, *h* exceeds that value, which calls into question the basic justification of the summary statistics (Mandelbrot, 1982).

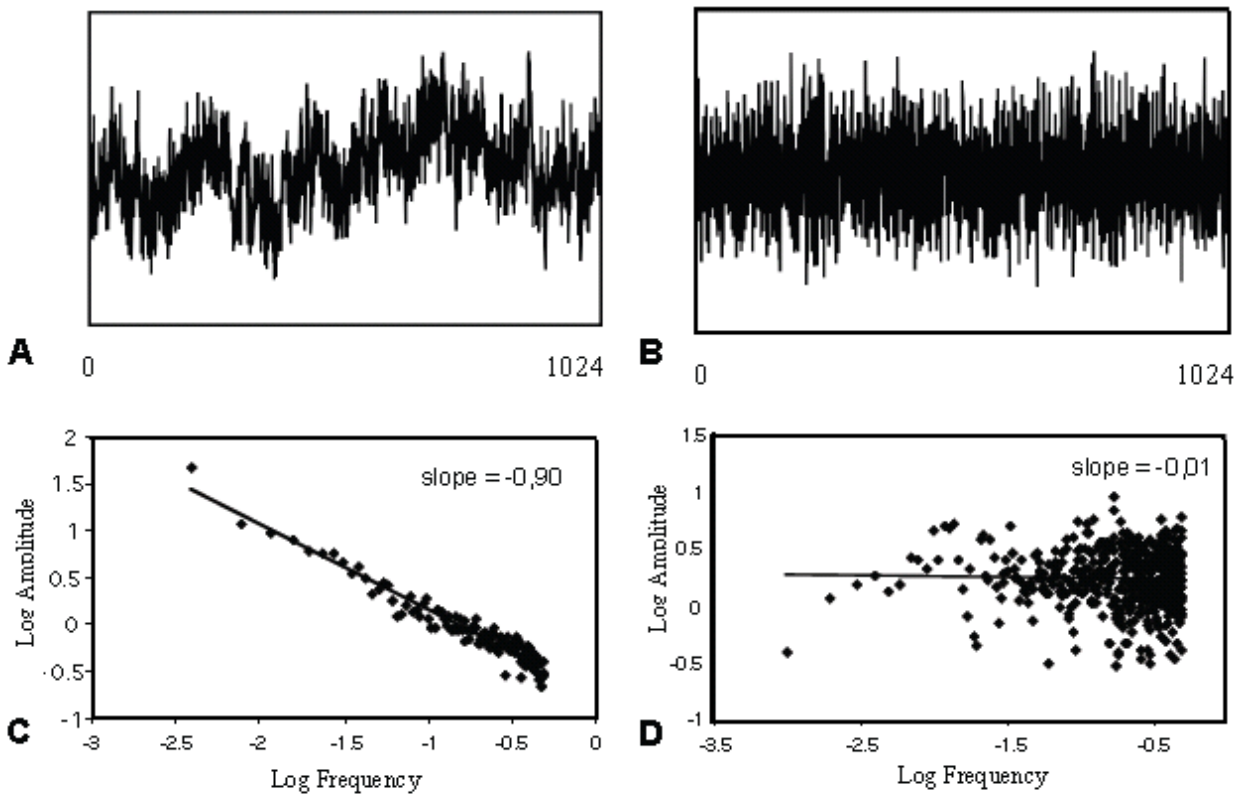

Figure 1. A typical example of 1/*f* scaling in an intact behavioral time series of one participant (a), and the same time series after randomization (b), and their respective power spectra (c and d). A slope of -1 indicates ideal 1/*f* scaling, a slope of 0 indicates random sequential ordering, see Method section.

1.1 Changing dynamics with motor learning

Although the occurrence of 1/*f* scaling is widely reported, the underlying mechanism remains an enigma throughout the physical, biological, and psychological sciences. Apart from its presence, tempting issues remain such as why the relative presence of 1/*f* scaling changes in different human performances. Whereas decreasing amounts of variability typically indicate improving levels of performance (e.g. Fitts, 1954), no such general statement can be made with respect to the temporal structure of variability in human performance. An important suggestion, however, is that the structure of movement variability may provide important clues regarding the compression of degrees of freedom into a controllable, low-dimensional coordinative structure (Mitra, Amazeen, & Turvey, 1998; Riley & Turvey, 2002; Turvey, 1990). In this article we pursue consequences of this suggestion.

The specific question of the present research is whether fractal patterns change after practice in precision aiming. Pointing or precision aiming is a long-established paradigm to study coordination of perception and action. In precision aiming, participants might move a pointer or a computer mouse between designated targets. In our experiment they move a stylus back and forth, repeatedly, between two targets on a digital tablet. In general, targets can be wide or narrow in diameter and closer or further apart, both of which affect performance. Fitts' law takes into account target width and the distance between targets to accurately predict movement-time central tendency, given accuracy greater than 96% (Fitts, 1954). The study that we report in this article used conditions yielding performance well below the 96% accuracy criterion. The purpose was to gauge changes in performance after motor practice in precision aiming. To further insure the opportunity for performance to improve, we required non-dominant hand performance.

Our specific interest is change in the structure of variation in movement times. This interest stems from recent developments in complexity theory and widespread observations of complex variation in perception-action tasks. Yet it remains to be discovered whether the structure of variation changes due to training in perception-action tasks.

We assume that 1/*f* scaling is a reflection of intrinsic self-organizing interaction-dominant dynamics (Van Orden et al., 2003). If so, then the logic of our experiment follows: first, 1/*f* scaling should be observed in movement time series of precision-aiming performance, as the phenomenon is claimed to be universal. Second, measured values of poor performance reflect less stable, less systematic coordinations of perception and action. Third, instabilities contribute unsystematic perturbations to measured values. Fourth, unsystematic perturbations add random variation to the signal of 1/*f* scaling as white noise. Fifth, each participant's time series should show reduced effects of random variation after practice, and more clear signals of 1/*f* scaling.

By using small targets, relatively far apart, and requiring the use of the non-dominant hand we induce less stable, less systematic coordination of perception and action. Because these conditions induce relatively poor performance overall, they also allow plenty of room for improvement with practice. The assertion is that improvement comes about by compressing the available degrees of freedom. Unfortunately inducing very poor performance overall reduces the possibility of reliably estimating directly the active degrees of freedom.

For instance, in the framework outlined by Mitra et al. (1998) we must expect to deal with the early phase of motor learning in which the system discovers and establishes the relevant collective variable. As they explain, in this phase there may be competing collective variables

and candidate subsystems at the level of the coordination pattern. In contrast, intermediate phases refine the interactions among subsystems that contribute to the victorious collective variable. Nevertheless, both early and intermediate phases of motor learning reduce active degrees of freedom, which we may discover indirectly in fractal, recurrence quantification, and sample entropy analyses.

As participants improve performance of the precision aiming task, we predict clearer examples of 1/*f* scaling in the movement time series. The rationale is that in learning, the many degrees of freedom for movement, that is, the available possibilities for the body to move between targets in precision aiming, are reduced to promote more efficient and coordinated performance (Bernstein, 1967). Movement will not be organized randomly, a situation in which all (indeterminate) degrees of freedom would be available. And movements will not be overly persistent (as in the sine wave), since contextual constraints on the kinematics of forthcoming movements are always dynamically changing. Apparent 1/*f* scaling is situated on the hypothetical border between persistence and "random" (chaotic) variability, between order and disorder. So, clearer instances of 1/*f* scaling should be observed with decreasing available degrees of freedom, as performance more reliably gauges variation near the border between order and chaos.

2. Method

2.1 Participants

The participants were fifteen undergraduate students who received course credit for participation. None suffered from any known motor impairment and all participants had normal or corrected to normal vision. All participants were right-handed as tested by the handedness subscale of the Lateral Preference Inventory (Coren, 1993).

2.2 Materials

Movement coordinates were recorded using a WACOM digitizer tablet connected to a regular Pentium PC. The tablet samples at temporal rate of 171Hz, with a spatial resolution of 1000 lines/cm. The input device was an inkless stylus used on a model sheet (A4) placed on top of the digitizer tablet. Kinematic records were converted into two dimensional coordinates using Oasis software (De Jong, Hulstijn, Kosterman, & Smits-Engelsman, 1996). Participants were seated on a height-adjustable chair in front of the digitizer tablet.

2.3 Procedure

In the present study, participants were invited to draw lines back and forth between two visual targets, as fast and as accurately as possible. The targets were presented on a printed sheet of paper, one at the left side of the paper and one at the right side. Participants were allowed to modify the distance to the digitizer tablet and the digitizer's orientation within a deviating range of 30° from the central position. The target width was 0.4 cm and the distance between targets was 24 cm. Five blocks of 1100 trials were completed with the non-dominant hand, all separated by three-minute breaks. When the last trial in a block was reached, a tone signaled the end of the block.

2.4 Data Analysis

Movement times between targets were treated as a time series. To quantify the temporal structure of the successive fluctuations, Spectral Analysis, Standardized Dispersion Analysis (SDA), and Detrended-Fluctuation Analysis (DFA) were conducted. To further investigate those results we fit the 1/*f* + white noise model of Thornton and Gilden (2005), conducted a Recurrence Quantification Analysis (RQA), and tested for sample entropy (SampEn). All analyses were performed using Matlab scripts.

Human time series data, like data from biological systems generally, are typically non-stationary noisy series containing extreme values. The tools available for fractal analyses must work around problems that come with such data. Known problems can be compensated for, which is why we used several methods together to estimate change across fractal statistics of practice blocks.

Some methods are complementary in that the strengths of each compensate for the weaknesses of the others. For instance, spectral analysis, while robust in many respects, requires extensive preprocessing of the signal and extreme observations can contaminate the outcome of the analysis (see Holden, 2005; Press et. al, 1992). Nonetheless they give a clear picture of 1/*f* scaling in the low frequency region of the spectral plot. Detrended fluctuation analysis is reliable and robust, and does not require the arbitrary setting of parameters, as does spectral analysis (Eke et al., 2002). Detrended fluctuation analysis can be applied to nonstationary signals and is not susceptible to most statistical artifacts or long-term trends, but it can falsely classify certain types of signals as fractal (Rangarajan & Ding, 2000). Standardized dispersion analysis is also highly reliable, but linear and quadratic trends may bias its output (we therefore remove both linear and quadratic trends for SDA). We insure reliable conclusions by using all three methods together.

An important advantage of RQA, unlike the aforementioned methods, is that this technique does not impose constraints on data set size. RQA does not make assumptions regarding statistical distributions or stationarity of data either. The challenge of applying RQA measures specifically as a complementary tool for fractal analyses is addressed in this paper.

2.4.1 Spectral analysis. Spectral analysis transforms data series from the time domain (milliseconds) into a frequency domain (Hz), through a Fast-Fourier-Transformation. The procedure finds the best-fitting sum of sine and cosine waves in a data signal, and renders their amplitudes and frequencies on log-log scales. The statistic of interest is the slope of the spectral portrait, which captures the relation between amplitudes and frequencies of variation in the data signal. A zero slope indicates non-random random structure in the signal, a slope of -1 indicates 1/*f* scaling. Spectral slopes as steep as -2 indicate fractional Brownian motion, the epitome of random walk processes.

Spectral analysis requires some preprocessing of the raw data (Holden, 2005). Extreme values were excluded (values below 50 ms and above 850 ms in the present case). Next, remaining outliers were removed if they lay outside a 3 x SD criterion. Finally, linear trends were removed and the remaining data were truncated to 1024 trials. The number of estimated frequencies was 512.

2.4.2 Standardized Dispersion Analysis (SDA). Dispersion analysis assesses the relative coherence of the patterns of fluctuations in 1/*f* scaling via the fractal-dimension statistic (see Holden, 2005). The Fractal Dimension (FD) is derived from estimating how variability changes with changing sample sizes. The dispersion analysis describes the changes in the

variability of a measurement across a range of sample sizes (or measurement resolutions), in terms of a power-law scaling relation. In other words, the dispersion analysis determines a scaling relation between sample size and sample variability. This relation is estimated in the slope of a regression line across successive estimates of how variability changes with sample size, in this case across six estimates. An FD of 1.5 indicates a random data series, whereas values approaching 1.20 indicate 1/*f* scaling.

2.4.3 Detrended Fluctuation Analysis (DFA). Detrended-fluctuation analysis (Peng et al., 1993) represents a relation between window sizes of data and the mean standard-deviations of the windowed data. First, the time series is subdivided into non-overlapping bins of equal length, and in each bin, the local trend -the locally best-fit line- is subtracted. Next, the root-mean-square of the locally detrended and binned timeseries is computed for windows of the same length. The process is repeated over increasing window sizes out to the limits of the finite data set. In the present study, DFA was performed on window sizes ranging between 4 and 1024. When the average fluctuation is plotted over the increasing window sizes on log-log scales, the slope represents the 1/*f* scaling exponent. A resulting scaling exponent equal to 0.5 would correspond to white noise. If the scaling exponent exceeds 0.5, the series has long range persistent correlations. In the case of a scaling exponent equal to 1, the sequence is scaled exactly as 1/*f*.

2.4.4 The 1/f + White Noise Model. The model proposed by Thornton and Gilden (2005) assigns data series the likelihood they originate from a fractal as opposed to Auto-Regressive Moving-Average (ARMA) process (cf. Wagenmakers, Farrell, & Ratcliff, 2004). This likelihood is based upon the comparison of a data set against model fitting parameters for whitened fractal noise (a mixture of 1/*f* scaling and Gaussian noise) as well as ARMA processes. These fitting parameters are given in separate reference libraries based on the 800 sampling distributions generated by the two candidate processes. The libraries encapsulate a reasonably complete range of spectral shapes that may be observed in either of the models. Based on maximum likelihood, the libraries are used to find the most likely source of an input data spectrum. Through this procedure, the classifier is able to decide whether a given data set is more consistent with a fractal or an ARMA interpretation. When this spectral classification framework favors a fractal interpretation, a 1/*f* + Gaussian noise model is tested. An advantage of this technique is that no prior assumptions are made concerning the nature of the data. In the present case, the 1/*f* + Gaussian noise model was generally preferred, and thus constitutes another test to determine changes due to practice. In particular, this model returns a specific test of whether white noise amplitude decreases due to practice.

2.4.5 Recurrence Quantification Analysis (RQA). RQA combines recurrence plots (Eckmann, Kamphorst, & Ruelle, 1987), that is, the visualization of trajectories in phase space, with the objective quantification of (non-linear) system properties. That is, time series are delayed with a certain lag (Takens, 1981) and embedded in a phase space with an appropriate dimensionality. Subsequently, complexity measures are quantified in that reconstructed phase space. This technique reveals subtle time-evolutionary behavior of complex systems by quantifying system characteristics in reconstructed phase-space.

RQA measures include recurrence (the percentage of data points that share a common area in phase space, dependent on a defined radius - the mean Euclidean distance separating data points in reconstructed phase space), determinism (the percentage of recurrent points that constitute line segments -recurrent patterns- parallel to the diagonal identity line in a recurrence plot), entropy (the Shannon entropy of the distribution of deterministic line

segments. The index is one way to quantify complexity of a deterministic structure), maxline (a measure of dynamical stability inversely proportional to the largest positive Lyapunov exponent, hence, attractor strength), and trend (the degree of nonstationarity). Detailed tutorials that include a careful examination of these parameters are (Marwan, Romano, Thiel, & Kurths, 2007; Riley, Balasubramaniam, & Turvey, 1999; Riley & Van Orden, 2005).

Parameters that affect the outcome of RQA measures, and thus need to be chosen carefully, are time lag or delay, and the embedding dimension. Here a delay of 3 was combined with an embedding dimension of 4. These choices were based on the first local minimum of the Average Mutual Information function (Fraser & Swinney, 1986) for the delay, and global False Nearest Neighbors (Kennel, Brown, & Abarbanel, 1992) for the embedding dimension. Another parameter is the minimal line length for identifying deterministic segments; here it was set to two points.

We applied a different RQA strategy than the one that typically is chosen. Traditionally, recurrence is identified by choosing first a fixed radius. We reversed that order, so that our a priori choice was the level of recurrence, not the radius. Instead of a fixed radius we used a fixed amount of recurrence (5%), and the resultant radius, for each participant, was the dependent variable. When a smaller radius is observed for the same level of recurrence, it implies that the absolute level of recurrence is higher.

2.4.6 Sample Entropy. Entropy measures have previously been used as an indirect gauge of the dynamical degrees-of-freedom in complex data signals (e.g. Newell, Broderick, Deutsch, & Slifkin, 2003; Slifkin & Newell, 1999). To compare the direction of change of the various indices of dynamical degrees-of-freedom described in the previous sections, sample entropy was computed (Richman & Moorman, 2000).
The Sample Entropy (SampEn) index indicates whether the dimensionality of the reconstructed attractor is increasing or decreasing. SampEn(*m,r,N)* is precisely the negative natural logarithm of the conditional probability that a dataset of length *N*, having repeated itself within a tolerance *r* for *m* points, will also repeat itself for *m* + 1 points, without allowing self-matches. SampEn measures generally range between 0 and 2; more random data sets produce a higher entropy value, and more regular data are reflected by lower values.
In the present SampEn analysis, we used parameter values of $m = 3$ and filter width of $r = 0.1$, where *m* is the length of compared runs of data and *r* is the proportion of the standard deviation used to filter the data (A detailed outline of the procedures for calculating SampleEn and determining its parameter values can be found in Richman & Moorman, 2000). Sample entropy has the advantage over approximate entropy because it is less biased (i.e., SampEn does not include self-matches), and more robust over a range of input parameters (see Lake, Richman, Griffin, & Moorman, 2002). The sample entropy, which is computed over the sequential values of the time series, should not be confused with the entropy in RQA, which is measured over the distribution of deterministic line segments in the recurrence plot.

3. Results

The discussion of the results starts with a summary of the traditional performance measures. These analyses pertain to successive movement times, their standard deviations, accuracy levels, and their changes with practice. Then, the results from the spectral and fractal analyses are presented, followed by the outcome of fitting the $1/f$ + white noise model. Then, the RQA outcomes are presented.

3.1 Aggregate performance measures

The overall mean movement time was 590 ms (± 80 ms). Not surprisingly, a repeated measures ANOVA across the 5 blocks of practice found decreasing mean movement times and standard deviations with practice (block: 1 (625 ms, *SD* = .09) vs. 2 (620 ms, *SD* = .08) vs. 3 (606 ms, *SD* = .08) vs. 4 (556 ms, *SD* = .08) vs. 5 (542 ms, *SD* = .07), very near the threshold for statistical reliability ($F(1, 14) = 4.51$, $p < .06$ and $F(1, 14) = 2.83$, $p < .06$ respectively); see Figure 2a. To further investigate these changes, difference contrasts were computed. For the movement times, the change between block 3 and block 4 was statistically reliable, $F(1,14) = 6.74$, $p < .05$. The movement times decreased even more in block 5, $F(1,14) = 5.70$, $p < .05$. The difference contrasts between the other blocks were not statistically reliable.

Each practice block was divided in four non-overlapping epochs of 256 data points to investigate possible changes in movement times within each block. Within the first and the fourth block, movement times decreased significantly between subsequent epochs, $F(3,42) = 6.74$, $p < .01$ and $F(3,42) = 5.95$, $p < .01$ respectively. Throughout the other blocks, the repeated measures ANOVAs where not significant. However, a careful examination of the data revealed that the difference contrasts between epoch 1 and 2 showed an initial drop in movement time (block 2: $F(1,14) = 4.82$, $p < .05$; block 3: $F(1,14) = 15.11$, $p < .01$; block 5: $F(1,14) = 5.95$, $p < .05$), after which movement times stabilized for the remainder of that block. Practice block did not reliably affect accuracy (block: 1 (15.37%, *SD* = 10.25) vs. 2 (14.40%, *SD* = 10.26) vs. 3 (15.23%, *SD* = 8.11) vs. 4 (13.93%, *SD* = 7.77) vs. 5 (12.13%, *SD* = 9.3), all $Fs < 1$).

3.2 Spectral and Fractal Analyses

The outcomes of spectral analyses, standardized dispersion analyses (SDA), and detrended fluctuation analyses (DFA), were subjected to repeated measures ANOVA's, to test for changes in scaling across blocks of practice. The spectral analyses all yielded slopes consistent with 1/*f* scaling, with average scaling exponents less than or equal to negative one. The main effect of block was significant ($F(4, 56) = 4.65$, $p < .01$), revealing a reliable linear trend with decreasing scaling exponents across practice blocks (the spectral slopes become steeper with practice), $F(1, 14) = 11.07$, $p < .01$. This pattern was confirmed by the SDA ($F(4, 56) = 3.55$, $p < .01$), revealing a reliable linear trend with decreasing fractal dimensions, $F(1, 14) = 9.74$, $p < .01$. Likewise the DFA revealed clearer examples of 1/*f* scaling with practice; over blocks, $F(4, 56) = 2.63$, $p < .05$, and a reliable linear trend with increasing scaling exponents, $F(1, 14) = 4.48$, $p < .05$.

To further investigate these effects, the mean difference contrasts between blocks were examined. Only the third and the fourth practice blocks differed reliably. For the spectral analysis, SDA and DFA, $F(1, 14) = 13.39$, $p < .01$; $F(1, 14) = 10.35$, $p < .01$; and $F(1, 14) = 6.73$, $p < .05$, respectively. Other blocks did not differ reliably from temporally adjacent blocks. The changes in the outcome of the spectral analysis, SDA and DFA are illustrated in Figures 2b, 2c and 2d respectively. Over blocks, the temporal variation in movement times became more clearly patterned as a 1/*f* signal.

To further investigate changes in scaling, within-block changes were estimated by subdividing the movement time series in four non-overlapping epochs of 256 trials. Delignières et al. (2006) showed that for simulated data series, reasonably reliable scaling estimates can be derived from a data series containing 256 trials. However, scaling outcomes

over such short time frames are more variable than outcomes over longer time frames. Within block 1, block 4 and block 5, none of the scaling estimates changed reliably, all F's < 1. In blocks 2 and 3, the different scaling estimates did not converge, likely because short time series are bound to reveal more variable indices. Within block 2, only SDA showed higher FD's (becoming less like ideal 1/*f* scaling) across epochs, $F(3,42) = 3.50$, $p < .05$. Throughout block 3, spectral exponents did increase (becoming more like ideal 1/*f* scaling) and the DFA exponents decreased (also becoming more like ideal 1/*f* scaling), $F(3,42) = 3.15$, $p < .05$ and $F(3,42) = 9.43$, $p < .001$ respectively.

3.3 The 1/f + White Noise Model

The spectral classification framework assigned a larger likelihood to the 1/*f* + white noise model for 82.7 % of the time series as opposed to an ARMA-model, $t(148) = -3.50$, $p < .01$. Thus, changes due to practice were only examined using fits to the 1/*f* + white noise model. Time series were first standardized and then transformed into an 8-point composite spectrum, averaged over participants, a procedure described by Thornton and Gilden (2005). The application of Thornton and Gilden's model showed a direction of change that was consistent with the other fractal scaling estimates. Although the spectral exponents suggested more pronounced fractal scaling after more blocks of practice, that increase was not statistically reliable, $F(4, 56) = 1.363$, p = .25. The random error term, however, did reliably decrease with blocks of practice, $F(4,56) = 2.99$, $p < .05$, as a statistically reliable linear trend over practice blocks, $F(1,14) = 5.25$, $p < .05$. This outcome is relatively direct support that random sources of variation decrease with practice, better revealing a 1/*f* signal. These outcomes are illustrated in Figures 2e and 2f.

3.4 Recurrence Quantification Analysis

RQA was performed to examine time-evolutionary properties of the time series that cannot be detected using scaling measures. Univariate repeated measures ANOVA's did not reveal reliable changes in radius with practice for the intact data (F (4,56) = 1.60, $p < .19$). (However, the difference contrast between block 3 and 4 was close to statistical reliability, $F(1,14) = 3.74$, $p < .08$). Also trend did not change over practice blocks, $F < 1$, indicating that data became neither more nor less stationary across blocks. All other RQA measures reliably increased across the blocks of practice ($F(4, 56) = 5.11$, $p < .05$ for determinism; $F(4, 56) = 75.36$, $p < .05$ for entropy; $F(4, 56) = 4.54$, $p < .05$ for meanline, and $F(4, 56) = 2.71$, $p < .05$ for maxline). Just as for the fractal measures, these differences occur specifically between block 3 and block 4.

Between blocks 3 and 4 difference contrasts revealed that determinism increases, $F(1, 14) = 9.71$, $p < .01$, as does entropy $F(1, 14) = 10.77$, $p < .05$, the average strength of attractor dynamics indicated by meanline $F(1, 14) = 7.90$, $p < .05$, and strength of the strongest attractor indicated by maxline $F(1, 14) = 5.10$, $p < .05$. No other contrasts were statistically reliable. However the decrease in RQA measures was close to the threshold for statistical reliability for both entropy $F(1,14) = 4.0$, $p = .07$ and maxline $F(1,14) = 4.12$, $p = .06$. In addition, a quadratic function gives a reliable fit across blocks 3, 4, and 5, for determinism $F(1, 14) = 5.25$, $p < .05$, entropy $F(1,14) = 6.13$, $p < .05$, and maxline $F(1,14) = 7.79$, $p < .05$, and although meanline did not reach threshold for reliability it is close and in the right configuration. We did not anticipate the overall downturn in RQA measures between blocks 4 and 5. The changing RQA values are shown in Figures 3a-3e.

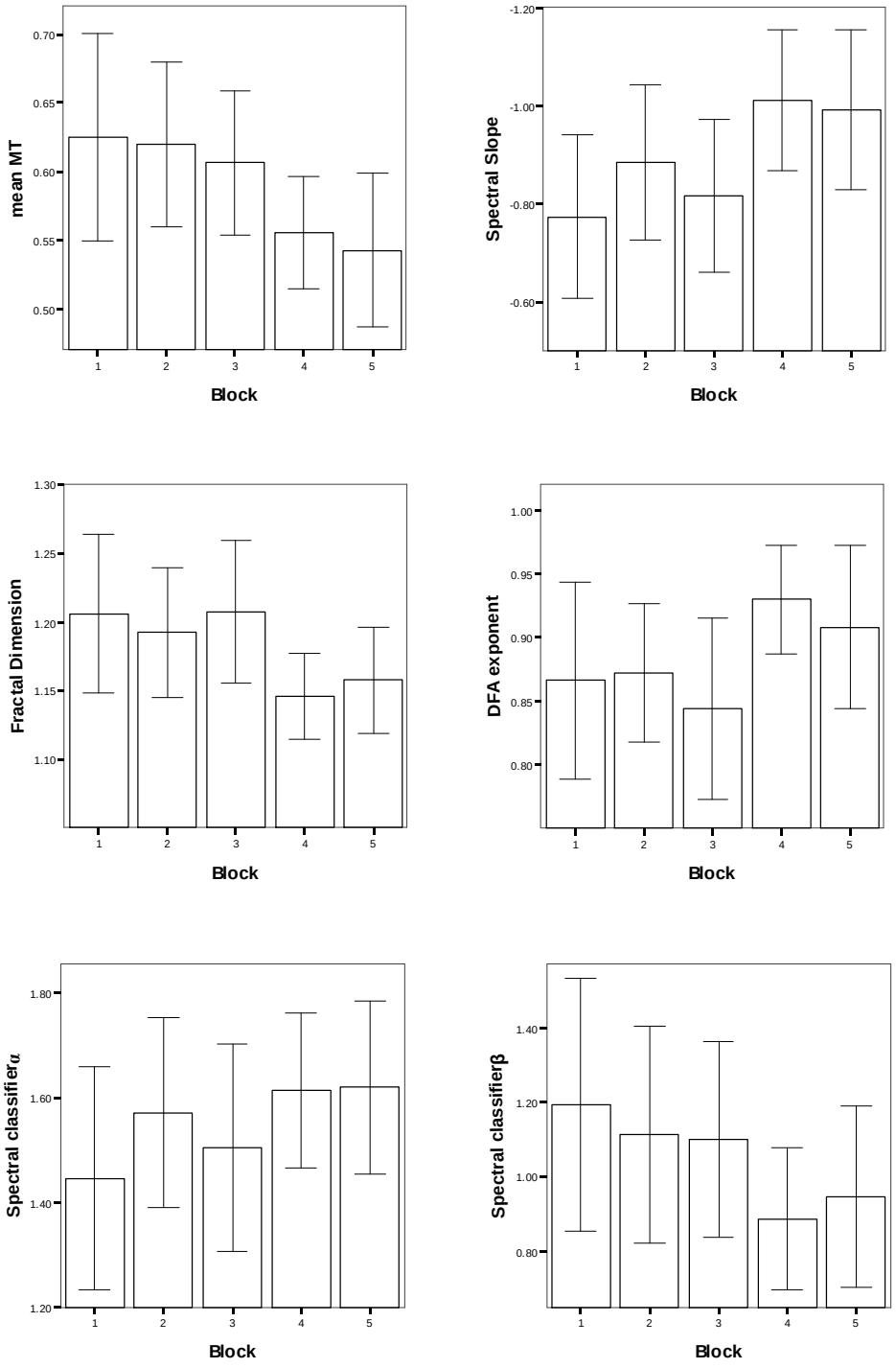

Figure 2. Changes in (a) movement time (b) spectral scaling exponent (c) fractal dimension, (d) DFA scaling exponent, (e) scaling exponent α and (f) error term β from Thornton & Gilden's (2005) fBmW model across blocks of practice.

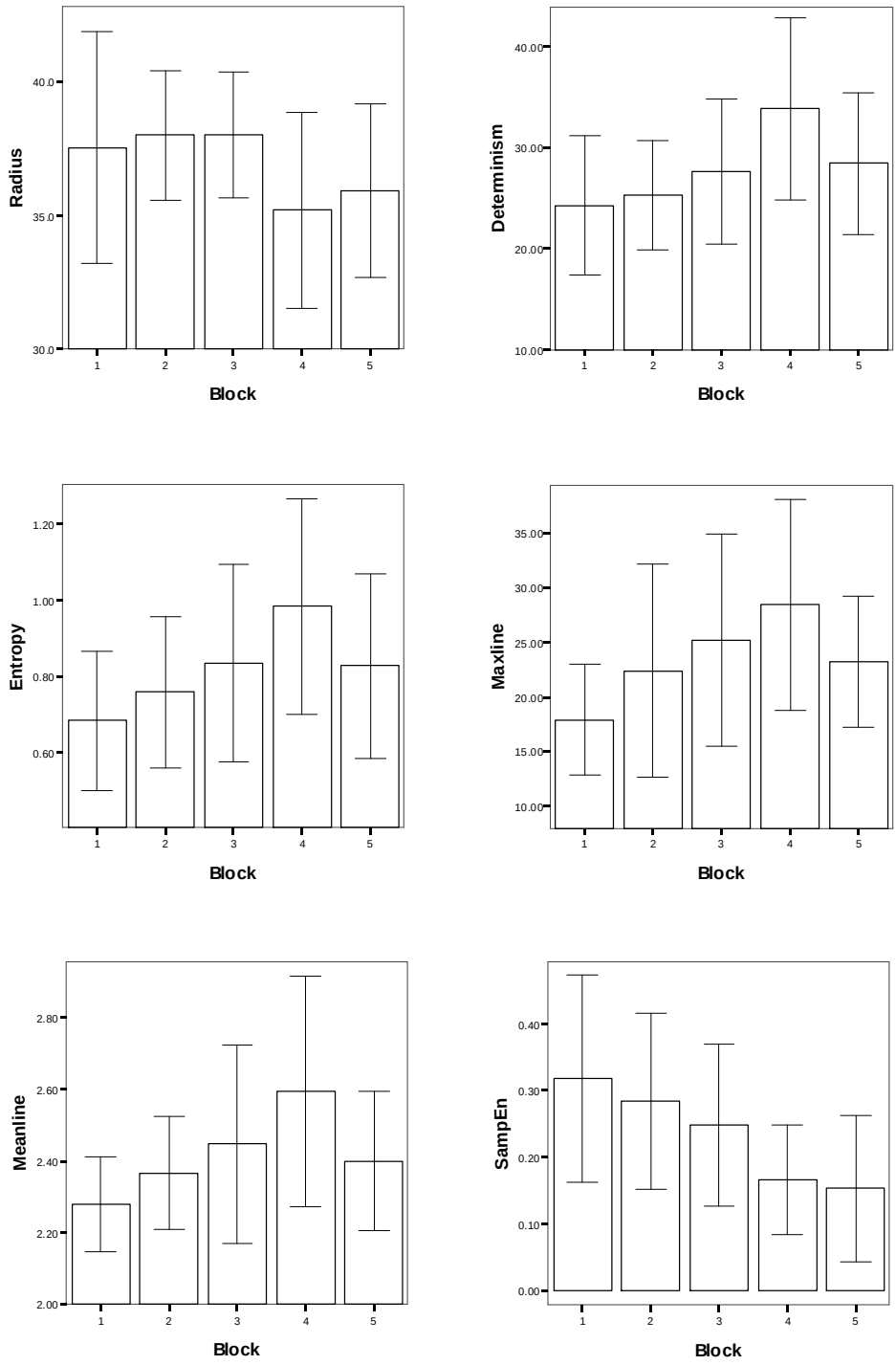

Figure 3. Changes in (a) radius, (b) the percentage of determinism, (c) entropy, (d) meanline, (e) maxline and (f) sample entropy across blocks of practice.

Most RQA measures change in the same direction across the first four blocks of trials and then reverse direction in the fifth block. By comparison, movement times decrease in the fourth block, and decrease even more in the subsequent fifth block. These changes are not a function of a speed-accuracy trade-off; the level of accuracy did not change. Perhaps the reversal of the global pattern of change in the last block is due to fatigue. While we cannot know this with certainty, it would contradict the idea that 1/*f* scaling itself is a fatigue

phenomena (e.g. Wagenmakers et al., 2004), and is worth pursuing in future work (with a sixth block for example), but we will not discuss this finding further without a replication.

To investigate possible within-block changes, data series were divided in four non-overlapping epochs of 256. RQA is a nonlinear tool, sensitive to details of the full time series analyzed, and smaller epochs do not necessarily combine to "equal" the outcome over an entire block. . Within Block 1, determinism, entropy, meanline and maxline dropped, and trend became less negative: ($F(3,42) = 4.26$, $p < .05$; $F(3,42) = 5.12$, $p < .01$; $F(3,42) = 4.22$, $p < .05$; $F(3,42) = 3.43$, $p < .05$; $F(3,42) = 6.57$, $p < .01$, respectively). The drop occurred especially between epoch 1 and 2 (an apparent start up transient, perhaps), the difference contrasts were $F(1,14) = 8.92$, $p < .05$; $F(1,14) = 12.16$, $p < .01$; $F(1,14) = 4.22$, $p < .05$; $F(1,14) = 12.56$, $p < .01$; $F(1,14) = 7.39$, $p < .05$, respectively. Otherwise, only one RQA parameter changed reliably; in block 3 trend changed to indicate that the data series became more stationary, $F(3,42) = 3.15$, $p < .05$.

3.5 Sample Entropy

The SampEn measures, like the RQA measures, effectively confirmed the anticipated direction of change in dynamical degrees-of-freedom (see Figure 3f). Over the five practice blocks, a repeated measures ANOVA revealed decreasing SampEn, $F(4,56) = 3.87$, $p < .05$. Also a linear trend was observed consistent with previous observations, $F(1,14) = 5.23$, $p < .05$. Within each block, changes in SampEn were investigated by dividing the data series in four non-overlapping epochs of 256 data points. However, no reliable within-block changes were observed. Also, none of the difference contrasts between epochs were statistically reliable in any of the practice blocks. Thus, SampEn gradually decreased across, but not within blocks.

4. Discussion

The primary finding of the present experiment is that movement time variability shows more consistent time-dependent properties in more practiced precision-aiming performance. Here, increasing skill with practice equals faster movement times, both within and between training blocks, without trading-off accuracy, plus increasingly clear 1/*f* scaling that also tracks the improving speed of performance. Changes in 1/*f* scaling exponents (and other fractal statistics) reliably track changes in the early phase of motor learning.

Our original prediction was thus confirmed. Practice better constrains and coordinates interaction-dominant dynamics, to reduce degrees of freedom, and so the structure of variation in movement times shows clearer signals of 1/*f* scaling. After practice movement dynamics became less random and more patterned. In reconstructed phase space, the attractive region became more deterministic and yielded a more complex structure (as indicated by higher entropy). Other recurrence quantification (RQA) measures indicated increasing system stability. And, after practice, a smaller radius captured the same percentage of recurrent attractor states (see Figure 3a), which, while not statistically reliable, replicates the pattern of the other variables, and suggests that movement trajectories evolve in a more confined region through their phase-space. Additional support for this claim comes from sample entropy (SampEn), which drops with practice indicating a lower-dimensional organization of coordinative structure. Thus practice adds constraints, which make the task more doable, or less difficult in a meaningful sense.

The difficulty of performing a motor task in a specific context generally is often estimated by self-report or physiological measures. Alternatively, levels of task difficulty are determined a priori based on reasonable assumptions about difficulty that may or may not be true. We assumed for example that task difficulty decreases with practice, and we then tracked practice effects using linear and non-linear tools in tandem, which revealed details of motor dynamics that converge in a consistent story about practice effects. Namely, intrinsic constraints acquired with practice change coordinative structures to reduce degrees of freedom. If this is true, then the relative presence of 1/*f* scaling may constitute a gauge for motor skill in closed motor tasks, and even difficulty or workload in human performance more generally. The latter possibility would conceive difficulty and workload as unsystematic perturbations on within-trial motor coordinations, and thereby random perturbations of 1/*f* scaling in repeated measurements.

The presence of 1/*f* scaling, in general, contradicts any view of motor coordination that regards variation in movement as uncorrelated noise imposed on a motor signal. Thus, the presence of 1/*f* scaling poses challenges to many conventional models of motor control (Torre, Delignières, & Lemoine, 2007). Specifically, for the present data, Fitts' (1954) original model, and more recent nonlinear models of precision aiming in the Fitts' task, have focused on central tendency, not time-evolutionary properties (e.g. Mottet & Bootsma, 1999; Flach, Guisinger, & Robison, 1996). The present results also contradict the conjecture that the relative strength of 1/*f* scaling increases with increases in task difficulty (Chen, Ding, & Kelso, 2001; but cf. Van Orden et al., 2003) and the conjecture that effects of task difficulty or skill are discarded per se by focusing on trial-by-trial variability (Wagenmakers et al., 2005).

In this regard, point to point movement times of each participant in every block of trials of the present precision-aiming task fluctuated in the fractal pattern of 1/*f* scaling. This outcome replicates previous wide-ranging demonstrations that motor variability entails fractal 1/*f* scaling. Structure and variation coexist in the time-evolutionary properties of motor behavior. This outcome reinforces the crucial empirical analytic point that one must include estimates of time-evolving structure of motor variability to derive an accurate picture of motor behavior (Liu, Mayer-Kress, & Newell, 2006; Riley & Turvey, 2002; Slifkin & Newell, 1999; Treffner & Kelso, 1999).

All these outcomes support the perspective taken here that 1/*f* scaling in motor (and cognitive) activity emerges from *interaction-dominant dynamics*. Reciprocally interactive processes interlink across time scales to change each other's dynamics and self-organize task performance (Van Orden et al., 2003). It is known that 1/*f* scaling is most clearly seen in measurements when external constraints are held constant, or changes are minimized (Gilden, 2001; Kello, Anderson, Holden, & Van Orden, in press). These are the conditions of the precision aiming task, which again reliably produced 1/*f* scaling. Yet understanding 1/*f* scaling as a reflection of self-organization is at odds with mainstream psychological science. The central issue in that argument is the logical possibility that 1/*f* scaling can appear as an exclusive consequence of ordinary linear dynamics acting in a somewhat extraordinary fashion. As we explain next, the outcome of the present experiment speaks to that argument as well.

Several independent sine waves plus random noise can be fitted to the gross pattern of a 1/*f* signal (Granger, 1980; Pressing, 1999; Pressing & Jolley-Rogers, 1997; Wagenmakers et al. 2004, 2005; Ward, 2002), as any pattern of variation can be linearly modeled after the fact (Beran, 1994). However, such a model must posit a special align parameter to integrate the

independent processes in the strict form of the scaling relation, or else must allow a primary role for coincidence.

The present results further complicate such an account because they demonstrate coordinated changes in the exact form of the scaling relation – practice converges across blocks on clearer patterns of 1/*f* scaling. Scaling exponents that estimate the overall structure of variation in movement times change with practice in a systematic fashion. In the linear framework, scaling exponents depend largely on the frequency and amplitude of variations in specific component processes. Thus, to account for systematic change in the exponent of 1/*f* scaling, linear models must add to their alignment parameter a capacity to moderate or control components to change together, to insure that their changes relative to each other maintain the 1/*f* relation between amplitude and frequency.

This extra capacity of a controller-component would join other ad hoc changes already implicated. For example, a linear model must introduce new components each time a longer data set is collected (Van Orden et al., 2005), and new components must be added when additional measurements are taken. Additional measurements of the same repeated performance yield additional uncorrelated streams of 1/*f* scaling (Kello et al., 2007; Kello et al., in press). In other words, 1/*f* scaling behaves like we expect a fractal phenomenon to behave; fractal time permeates collected data to their full extent. All these facts are unexpected from linear models (Bak, 1996; Bassingthwaighte, Liebovitch, & West, 1994; Liebovitch & Todorov, 2000; Thornton & Gilden, 2005).

The interpretation of the presented results in terms of interaction-dominant dynamics generates further insight into the nature of control and coordination in perception and action. As constraints accrue with practice, new lower-dimensional modes of intrinsic dynamics arise, which reduce the intrinsic degrees-of-freedom, Scaling exponents move closer to the -1 scaling exponent of hypothetical 1/*f* scaling because practice is a means to add constraints in behavior and reduce degrees of freedom for behavior, and thereby reduce across-trial and within-trial sources of random variation in measures of behavior.

Skilled and unskilled movements emerge to satisfy the constraints, extrinsic and intrinsic, of the task at hand. Movements are not solutions to a mechanical equation. Reliable changes in 1/*f* scaling for identical task conditions suggest dynamics modulated by the coupling of task and participant, not just by properties tasks. Parallel changes between fractal, complexity, and traditional performance measures motivate this claim and previous findings also support this conclusion (Pressing & Jolley-Rogers, 1997). Thus fractal dynamics are informative about task complexity, but complexity must take into account both task and participant.

This brings us to a final question. Why 1/*f* scaling? Why do added constraints, that better coordinate the dynamics of brain and body with the dynamics of task requirements, yield scaling exponents closer to the ideal form of 1/*f* scaling? 1/*f* scaling is the idealized pattern of interaction-dominant dynamics that separates chaotic variation from rigid order. 1/*f* scaling is also the idealized pattern of interaction-dominant dynamics that never strays far from choice points, or critical points. This insures flexibility to adjust kinematics even as behavior is realized and even to produce entirely novel kinematics when necessary.

Flexibility also equals vulnerability with respect to inevitable and ubiquitous perturbations of measured behavior, of all sorts. Such perturbations contribute random variation, which will whiten the signal of 1/*f* scaling. Interaction-dominant dynamics perturbed to be less near critical points and more toward chaotic dynamics will appear empirically as a whitened 1/*f*

signal. If these hypotheses are reliable, then 1/*f* scaling-exponent will soon be widely recognized as an index or order parameter of coordination in human performance.

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Chapter 3

Nested timescales of motor control: A trade-off study

Based on:

Wijnants, M. L., Cox, R. F. A., Hasselman, F., Bosman, A. M. T., & Van Orden, G. (2012). A trade-off study revealing nested timescales of constraint. *Frontiers in Fractal Physiology, 3*, 116. doi: 10.3389/fphys.2012.00116

Wijnants, M. L., Bosman, A. M. T., Cox, R. F. A., Hasselman, F., & Van Orden, G. (2011). Nested timescales of motor control: a trade-off study. In E. Charles & L. J. Smart (Eds.), *Studies in Perception and Action XI* (pp. 116-120). Philadelphia, PA: Taylor & Francis Group, LLC.

CHAPTER 3

Abstract
This study investigates human performance in a cyclic Fitts task at three different scales of observation, either in the presence (difficult condition) or in the absence (easy condition) of a speed-accuracy trade-off. At the fastest scale, the harmonicity of the back-and-forth movements, which reflects the dissipation of mechanical energy, was measured within the timeframe of single trials. At an intermediate scale, speed and accuracy measures were determined over a trial. The slowest scale pertains to the temporal structure of movement variability, which evolves over multiple trials. In the difficult condition, reliable correlations across each of the measures corroborated a coupling of nested scales of performance. Participants who predominantly emphasized the speed-side of the trade-off (despite the instruction to be both fast and accurate) produced more harmonic movements and clearer 1/*f* scaling in the produced movement time series, but were less accurate and produced more random variability in the produced movement amplitudes (vice versa for more accurate participants). This implied that speed-accuracy trade-off was accompanied by a trade-off between temporal and spatial streams of 1/*f* scaling, as confirmed by entropy measures. In the easy condition, however, no trade-offs nor couplings among scales of performance were observed. Together, these results suggest that 1/*f* scaling is more than just a byproduct of cognition. These findings rather support the claim that interaction-dominant dynamics constitute a coordinative basis for goal-directed behavior.

1. Introduction

Trade-off phenomena emerge when human performance reaches its limits, and the trade-off between speed and accuracy especially, has played an historic role in the study of cognitive performances. Speed-accuracy trade-offs entail that faster actions are performed less accurately, while more accurate actions are executed more slowly, and have been a topic of study for more than a century (Woodworth, 1899). Nevertheless, the origins of speed–accuracy trade-offs are still debated. This study aims to describe a speed-accuracy trade-off in terms of interacting constraints, which are nested across different timescales of performance.

Our interest in nested constraints is motivated by the fact that well-coordinated behavior consists of dynamic sequences that evolve simultaneously on slower or faster timescales (cf. Pattee, 1973). For instance, in an everyday conversation, a conversant will produce syllables, themselves contained in words, which in turn are contained in sentences. The events that equate pronouncing a syllable (fast), word (slower) or sentence (slowest) unfold on different timescales. The involved timescales of control extend to around 70 muscles that must coordinate to pronounce a single syllable (Turvey, 2007), as well as to the postural sway and eye movements of speakers that become coupled in their conversation (Shockley, Santana, & Fowler, 2003; Richardson, Dale, & Kirkham, 2007). All these correlated events (e.g., producing an utterance, word, or sentence, leaning forward or backwards, etc.) exist across nested timescales of change, from milliseconds to minutes or possibly hours, although they are coupled, nonetheless, in a highly constrained coordinated activity of speech to enact a conversation.

The example of a conversation aims to show that coordinating listening and speaking means properly sequencing events across a hierarchy of timescales. With these multiple timescales present in any example of behavior, the challenge is to identify the general principles of coordination in systems of such complexity. A good place to start investigating how behavior

becomes so precisely ordered spatially and temporally is at the limits of task performance. It is in behavioral regimes where incompatible constraints are imposed on performance where trade-off behaviors emerge, and where the different timescales of changing constraints are likely to reveal themselves in most detail.

In this study, we employ a cyclic precision-aiming task that has a long history in psychology (Fitts, 1954), allowing a solid empirical ground on which to begin to describe the nested sources of constraint within a speed-accuracy trade-off. In this task, participants are typically instructed to move a pen or stylus as fast and as accurately as possible back and forth between two visual targets. Arguably one of the most robust models of speed-accuracy in goal-directed movements, Fitts' law, describes the relation between the duration of accurate movements *MT* and the precision constraints of the task, namely the target size *W* and the movement amplitude *D* between the targets; $MT = a + b \log2 (2D/W)$.

Note that movement time and accuracy describe performance at the timescale of aggregate single trial outcomes. Consequently, Fitts' original model made no predictions about the movement trajectories enacted within a trial. The study of speed-accuracy trade-offs has historically been tied as well to the kinematics of movement trajectories (i.e., changes in displacement, velocity, and acceleration over time or position), however. Increasing accuracy requirements, for instance, leads to systematic changes in movement kinematics (e.g., the deceleration phase lengthens for more narrow targets, time to peak velocity is scaled to movement amplitude, etc.; Adam, 1992). The speed-accuracy trade-off thus yields contingencies that couple the timescale of single trial outcome measures (as expressed by aggregate speed and accuracy measures), to the faster changing kinematics enacted within a single movement.

Here, we further pursue the suggestion that constraints at one timescale interact with and may therefore trade-off against constraints at a slower or faster timescale. This entails contingencies of trade-off phenomena that compose horizontal couplings (within a timescale: i.e., speed versus accuracy) as well as vertical couplings (across timescales: i.e., speed or accuracy versus movement kinematics). The present study tests whether such couplings extend to the temporal structure of observed variability in sources of constraint evolving on timescales slower still than the trial-by-trial scale of average speed or accuracy (Gilden, Thornton, & Mallon, 1995; Gilden, 2001; Hausdorff, 2007; Riley & Turvey, 2002; Slifkin & Newell, 1998; Van Orden, Holden, & Turvey, 2003).

Figure 1 presents the different levels of analysis included in this study, each of which pertains to a different measurement of performance. The top part of Figure 1 pertains to the fastest timescale of the Fitts task. It shows acceleration profiles that reveal the biomechanical constraints that operate on kinematic parameters within the movement trajectories of a Fitts task performance. The middle part of Figure 1 pertains to an intermediate measurement scale of speed and accuracy measures, which summarize an entire movement outcome and directly reveals the degree of task-compliance. The bottom part of Figure 1 pertains to the slowest changes occurring over multiple trial outcomes across the entire Fitts task session, as it shows two time series with a distinct sequential structure of variability over many trials.

By investigating a perceptual-motor task simultaneously at three different scales of observation, we expect linkages within and between these scales. If control is indeed distributed over intertwined timescales, that would challenge the conventional assumption, however, that the locus of human control is encapsulated in discrete components that each

solve their own problems along a single common timescale (cf. Simon, 1973). And in fact, there exist good arguments to support the idea that the many free variables of the skeletomuscular system are not controlled individually (Bernstein, 1967; Turvey, 2007). For instance, in natural and artificial self-organizing systems, simple coupling rules at the level of the individual components of the system can result in overall coherent behavior (Bak, Tang, & Wiesenfeld, 1987; Prigogine & Stengers, 1984).

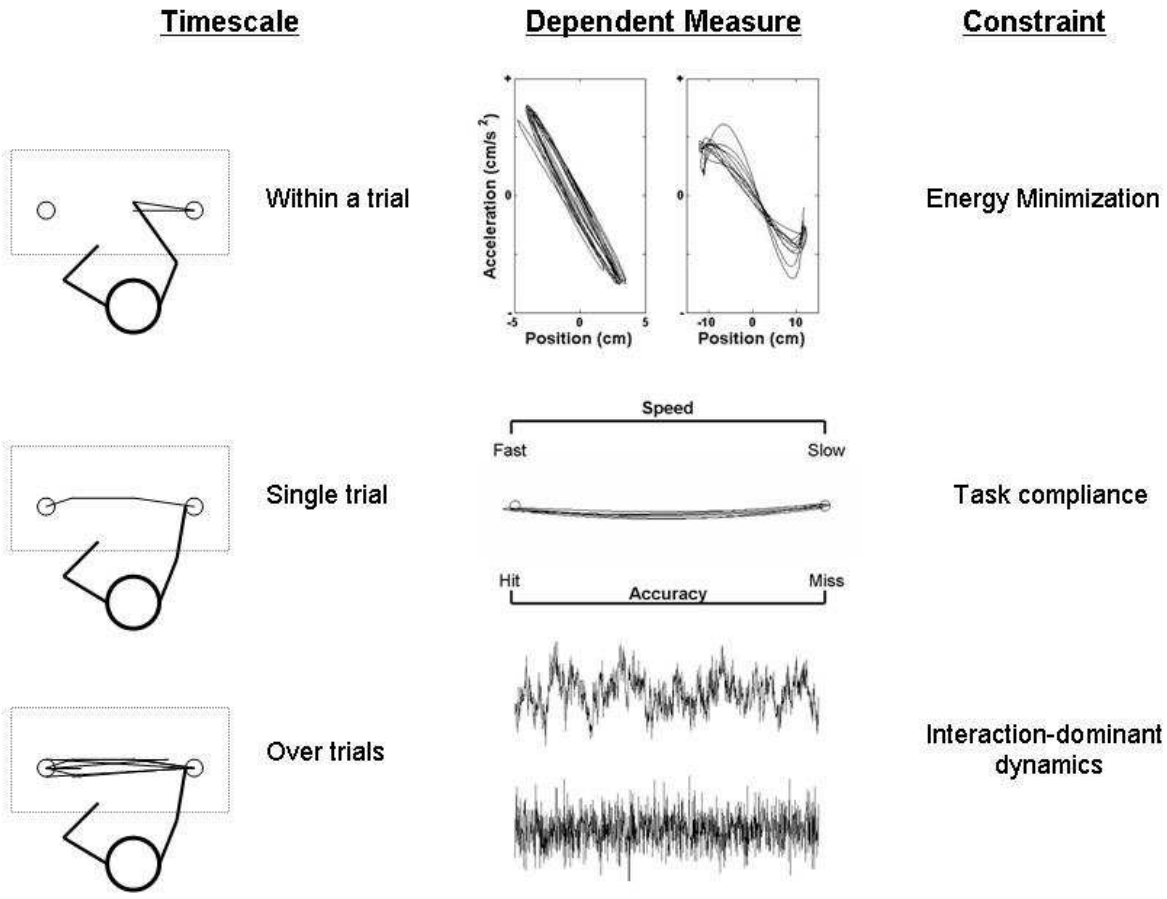

Figure 1. Three interlinked measurement scales are shown. The top part represents an example of performances evolving within the timeframe of a movement (finest scale). The middle part pertains to performances at the level of a movement outcome (intermediate scale). The bottom part concerns dynamics evolving over sequences of multiple trial outcomes (coarsest scales).

1.1 Movement Kinematics

The spatial and temporal details of movement trajectories constitute a rich source of information about the organization of human movement. This fine observational scale of movement analysis contains details which are lost at the coarser scale of a movement outcome as it provides information on how muscles act to generate and degenerate kinetic energy in the moving arm within the timeframe of an entire movement. Kinematic descriptions of movement patterns have a long history in the study of motor control and have substantially fueled the debate on trade-off phenomena. In this study we limit our interest in movement kinematics to a physical description of the dissipation of mechanical energy in rhythmical movements.

Specifically, rhythmical movements can be described precisely in physical terms of a self-sustained oscillation (e.g., Beek, Schmidt, Morris, Sim, & Turvey, 1995; Haken, Kelso, & Bunz, 1985; Kay, Saltzman, Kelso, & Schöner, 1987; Kelso 1995; Kugler & Turvey 1987). As an example, consider a mass-spring system without friction. If the system is at rest at the equilibrium position then there is no force acting on the mass. If the mass is displaced from the equilibrium position, a restoring (elastic) force F (potential energy) is exerted by the spring in the form of: $F = -kx$ (Hooke, 1678; known as Hooke's law), where k is a spring constant, and x is the displacement from the equilibrium position. The negative sign means that the elastic, restoring force always acts in the opposite direction of the displacement. In other words, when the system is displaced from its equilibrium position, mass will start oscillating in a sinusoidal fashion (called simple harmonic motion) because an elastic restoring force which obeys Hooke's law tends to restore the system towards the center of displacement. This means that velocity is maximal at the center of the movement (equilibrium position) and minimal at the turning points, while acceleration is maximal at the turning points, and minimal at the center. Thus, if rhythmical movements reveal simple harmonic motion, the oscillator energetically self-sustains itself, hence the term self-sustaining oscillator.

Under certain conditions, typically involving low precision constraints, a moving limb in a cyclic Fitts task acts as a linear oscillator and thus displays simple harmonic motion (e.g., Mottet & Bootsma, 1999). Rhythmical movement thus exploits the elastic properties of the neuromuscular system, much like a mass-spring system. This means that when the moving arm, hand and shoulder are stretched to the left, it pulls back to the right near reversals, because muscular and other tissues function as the spring that elastically stores and releases mechanical energy (Turvey, 1990). In other words, kinetic energy that is lost towards the end of each movement is stored in a potential, elastic form at the natural biomechanical turning points of the limbs to the benefit of the next half-cycle of movement (Guiard, 1993). Unlike the mass-spring example however, human movement is susceptible to friction and consequently mechanical energy is lost in each movement cycle. A self-sustained linear oscillator must therefore overcome the energy loss due to friction to sustain cyclic motion (see Kugler & Turvey, 1987, for a detailed description).

Figure 2a shows 20 low precision-constrained movement trajectories (targets are 2 cm wide and 8 cm apart) that reveal simple harmonic motion, and hence, obey Hooke's law. Figure 2c shows that changes in velocity with changes in displacement (called a phase portrait) are circular, typical for a linear oscillator: maximal velocity is reached at the center of the movement where acceleration is minimal (see Figure 2e), and maximum acceleration is reached at movement reversals where velocity is minimal. The smooth cyclic motion requires only a modicum of fresh energy to sustain the trajectory to the next target, thus dissipating little mechanical energy because of the elastic restoring force.

Highly precision-constrained movements, in contrast (as shown in Figure 2b; targets are 0.4 cm wide and 24 cm apart) typically require strong deceleration when approaching a target, and thus display inharmonic motion. In physical terms, the self-sustained oscillation becomes dampened as mechanical energy is dissipated by decelerating towards the target (see Figure 2d and 2f). This means that the mechanical energy that cannot be recovered in potential form (because it is dissipated) needs to be re-inserted each time a participant re-accelerates towards the next target. The relative degree of harmonicity in the kinematics of rhythmical movement

thus offers a physical description of the recycling of kinetic energy in potential form, which acts as a biomechanical constraint on speed-accuracy trade-off in cyclic movements.

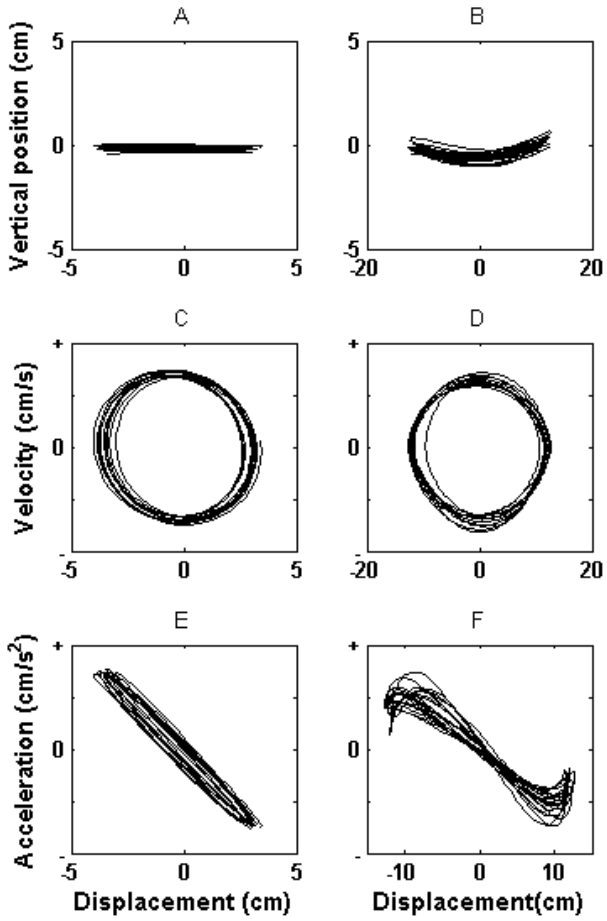

Figure 2. Panel a depicts 20 harmonic half-cycles (the circular targets were 2 cm wide and 8 cm apart) produced by one representative participant during the course of the experiment. Panel b shows 20 inharmonic half-cycles produced by another representative participant in a condition where targets were 0.4 cm wide and 24 cm apart. Panel c of the participant who produced the harmonic half-cycles reveals a circular phase portrait typical for a linear oscillator, whereas panel d of the participant who produced inharmonic half-cycles shows a damped phase portrait. The respective acceleration (Hooke's) portraits for the harmonic and inharmonic movements are presented in the respective panels e and f. Note the different scale on the x-axes.

1.2 Long-range dynamics

When people perform cyclic movements, there is always cycle-to-cycle variability. The variability of goal-directed behavior may in fact be one of its most prominent characteristics: Individual movement cycles are never exact duplicates of one another. The conventional assumption is that movement variability is a product of unstructured (random, Gaussian) noise, superimposed on a deterministic signal. That is, trial-ordered dynamics are usually conceived as a statistical nuisance, providing minimal, if any, insight into the nature of coordination, apart from the magnitude of white noise (e.g., standard deviation).

Over recent decades, however, it has become clear that movement variability rarely equates with white noise, and that temporal variability is usually structured and reveals specific details

of the system dynamics (Gilden, 2001; Riley & Turvey, 2002; Slifkin & Newell, 1998; Stergiou & Decker, 2011; Torre & Balasubramaniam, 2011). In fact, structured variability appears to be the rule rather than the exception, and is often more revealing than aggregate information in terms of unpacking the nature of the system organization (Ihlen & Vereijken, 2010; Kello, Beltz, Holden, & Van Orden, 2007; Kiefer, Riley, Shockley, Villard, & Van Orden, 2009; Konvalinka et al., 2011; Wallot & Van Orden, 2011a).

Nevertheless, the nature of cognitive dynamics still remains a much debated topic. Some scientists prefer to retain that long-range dynamics are only a byproduct, which is neither detrimental nor particularly useful to inquiry (Wagenmakers, van der Maas, & Farrell, 2011). Others have suggested that structured variability is a fundamental, functional feature, playing a crucial role in the coordination of perception and action (Kello et al., 2007; Van Orden et al., 2003; Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009). Here we pursue the latter suggestion by investigating the *fractal scaling* properties and *entropy* of spatial and temporal long-range dynamics, both in the presence and in the absence of speed-accuracy trade-off.

1/f scaling. 1/*f* fluctuation presents an intriguing phenomenon that has received a growing interest in biology, psychology, and movement sciences during the last decade. It is a describing property of the trial-by-trial variability of a time series, observed during repeated human performances. Fractal processes like 1/*f* scaling have the characteristic of self-similarity, which means that similar statistical features are observed across different temporal or spatial scales. The fractal pattern of variation can, for instance, be portrayed in a spectral analysis. This involves transforming a time series into the frequency domain by Fourier analysis, which represents the series as a set of sine waves, each with an associated frequency (how often changes of a particular size occur) and power (the size of changes across measured values). 1/*f* scaling of a time series means that changes in power are typically small at the highest frequencies (i.e., extending over few trials), but that those changes are embedded in overarching, lower frequent changes of higher amplitude spanning over many measurements. 1/*f* scaling thus composes a nested pattern of response variability across scales; a time series plot of 1/*f* fluctuations has the same “look and feel” as one zooms in or out to see more fine-grained or coarse-grained features of the fluctuations (e.g., see Wallot & Van Orden, 2011b).

Statistically, a 1/*f* scaling relation can be expressed as a relation between the size of changes (power), and how often changes of that size occur (frequency), which is inversely proportional on logarithmic scales. Figure 3 presents three types of temporal variability (i.e., noise) of a time series accompanied by their respective power spectra. The top part of the figure represents a data series with random background noise. A data series with random background noise, as traditionally assumed in many statistical analyses, does not yield a relationship among frequency (*f*) and a particular change of amplitude S(*f*) in the signal. The middle part of the figure represents a time series that is very close to ideal 1/*f* scaling, and can be parameterized by an exponent α, as $1/f^{\alpha}$, where α is 1 for ideal 1/*f* scaling, and 0.98 for the example time series. The bottom part of the figure is called Brownian noise and can be described as $1/f^2$ noise. Brownian noise is also called a random walk, because it can be produced by adding a random increment to each sample to obtain the next. In contrast to white noise, which can be produced by randomly choosing each sample independently, Brownian noise yields persistence or memory in the data series.

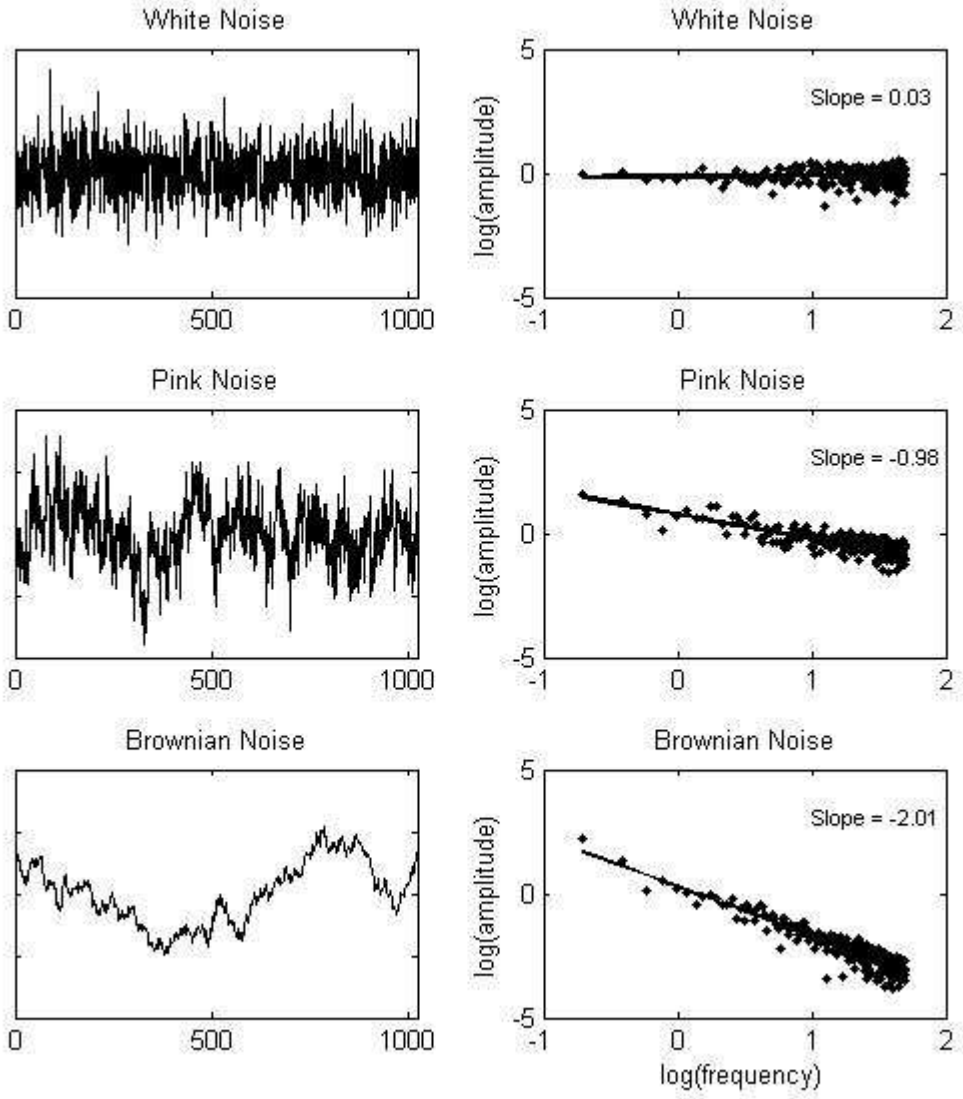

Figure 3. Three different classes of temporal variability, white noise (upper left panel), 1/*f* scaling (middle left panel), and Brownian noise (lower left panel), and their respective power spectra are shown in the respective panels at the right.

To date, dozens of studies have been published on 1/*f* scaling in cognitive and motor performance, all demonstrating widespread, perhaps ubiquitous fractal dynamics (e.g., Diniz et al., 2011; Van Orden, Kloos, & Wallot, 2011, are reviews). Typically, repeated human behaviors show a scaling exponent α in the range of 0 and 1, in between random noise and 1/*f* scaling. Examples of cognitive tasks include mental rotation, lexical decision, and visual search (Gilden, 2001), simple reaction time and word-naming (Van Orden et al., 2003), forearm oscillation (Delignières, Torre, & Lemoine, 2008), synchronization to a metronome (Chen, Ding, & Kelso, 1997); implicit associations (Correll, 2008), bi-daily reports of self-esteem (Delignières, Fortes, & Ninot, 2004), and movement times in a Fitts task (Valdez & Amazeen, 2008; Wijnants et al., 2009), among others. But sometimes α varies between 1 and 2 or even beyond, often in continuous processes like postural sway (e.g., Collins & De Luca, 1993), force production (Sosnoff, Valantine, & Newell, 2009), or galvanic skin response (Wijnants, Cox, Hasselman, Bosman, & Van Orden, 2012).

Although 1/*f* scaling has been observed throughout human physiology and behavior in varying degrees, its origin and meaning remains unclear (Diniz et al., 2011; Van Orden, Holden, & Turvey, 2005). One position in the debate is that 1/*f* scaling is a typical behavior of self-organizing systems, which reflects a fundamental aspect of all physiological and cognitive functions: Their emergence in the balance of independent versus interdependent component activities. In recent years, there has been a growing empirical support for the position that 1/*f* scaling may indeed result from the interaction of many ongoing processes over a multiplicity of interdependent scales, thereby serving as a coordinative basis of cognitive function (e.g. Kello et al., 2007, Kello, 2011; Van Orden et al., 2011; Wijnants et al., 2009). That is, 1/*f* scaling is usually seen most clearly in well-coordinated behaviors, and less clearly in non-optimal performance or with aging and disease (e.g., Goldberger et al., 2002; West, 2006).

For instance, deviations from 1/*f* scaling, either towards white noise or towards Brownian motion, have been found with epilepsy (Ramon, Holmes, Freeman, McElroy, & Rezvanian, 2008), heart failure (Goldberger et al., 2002), fetal distress syndrome (Goldberger, 1996), major-depressive disorder (Linkenkaer-Hansen et al., 2005), mania (Bahrami, Seyedsadjadi, Babadi, & Noroozian, 2005), attention-deficit-hyperactivity-disorder (Gilden & Hancock, 2007), developmental dyslexia (Wijnants, Hasselman, Cox, Bosman, & Van Orden, submitted), autism (Lai et al., 2010), Alzheimer's disease (Abásolo, Hornero, Gómez, García, & López, 2006), Huntington's disease (West, 2006), Parkinson's disease (Hausdorff, 2007), and even slow transit constipation (Yan, Yan, Zhang, & Wang, 2008), among other examples. In each of these studies, healthy controls revealed long-range dynamics reliably closer to 1/*f* scaling in the respective variables of interest.

These examples have been paralleled by manipulations of task constraints as well. For instance, the presence of 1/*f* scaling increases as performance becomes more proficient with learning (Wijnants et al., 2009), yet may sometimes decrease as task demands increase (Clayton & Frey, 1997; Correll, 2008; although cf. Kloos & Van Orden, 2010). The presence of 1/*f* scaling also correlates with the severity of a reading impairment (Wijnants et al., submitted), depression symptoms (Linkenkaer-Hansen et al., 2005), the success rate of recovery from traumatic brain injury (Burr, Kirkness, & Mitchell, 2008), the severity of Huntington's and Parkinson's symptoms (Van Orden, 2010) and falling risk in elderly (Hausdorff, 2007). In each of the cases more flexibly stable, adaptive, or coordinated behaviors showed clearer 1/*f* scaling.

These studies raise the suggestion of close linkages between fractal dynamics and coordination in human physiology and cognition, and with these precedent studies in mind we employ 1/*f* scaling as a performance index of coordination in a Fitts task (cf. Miyazaki, Kadota, Kudo, Masani, & Ohtsuki, 2001; Valdez & Amazeen, 2008) to investigate speed-accuracy trade-off. Far from being a statistical artifact or 'just' unexplained variance, fractal patterns may actually be a signature of strongly emergent coordination. If so, one may expect 1/*f* scaling measures to be sensitive to the task-specific constraints that are in play in a trade-off among performance measures.

Entropy. We complement our analyses of long-range dynamics by assessing the entropy of the data signals, which provides a complementary way of characterizing the presence of temporal structure in a time series. A measure of entropy summarizes the degree of predictability of a time series, which is the likelihood that similar observations (i.e., observations within a specified range of measurement values) are followed by a number of

additional observations within that range. Entropy can thus be conceived as a measure of orderliness. The entropy of a system increases as it becomes more disordered or random, and decreases as it becomes more patterned (i.e., shows increased temporal order, as in 1/*f* scaling). This means that changes in entropy provide a potential window into self-organizing control in complex systems, because self-organization can be considered as a spontaneous tendency of a system towards order and entropy is a measure of the disorder of a system.

In other words, time series containing coherent dynamical structure are expected to yield lower entropy than less predictable (i.e., random) time series. Nonetheless, reduced entropy is far from an exclusive criterion for self-organization. For instance, trivially uniform or periodic signals would yield even lower entropy (i.e., high self-similarity on a fixed scale) than would be expected from the behavior of a self-organizing system that is scale-free. That is, self-organizing systems arguably live near the midpoint of a scale that ranges from independent random variables (i.e., high entropy) to static or periodic variables (i.e., low entropy). Inconveniently, there is neither a clear-cut midpoint nor an absolute scale of entropy in terms of cognitive activities. Therefore, we use entropy here solely as a check of convergence in direction of change with 1/*f* scaling measures. Although the extent of 1/*f* scaling should be honest in itself, a measure of entropy provides an additional reliability check of the deviations from randomness that are expected in the performances of low-dimensional, self-organizing systems constrained across multiple scales of degrees-of-freedom.

1.3 Hypothesis

Here, we employ the classic paradigm of precision aiming to investigate speed-accuracy trade-off in goal-directed behavior. We presented participants with a Fitts task and instructed them to move as fast and as accurately as possible back and forth between two circular targets for a prolonged time (1100 half-cycles). The resultant movement coordinates were analyzed at three different measurement scales of performance. The finest scale yields a measurement of the movement kinematics (within-trial). This description of performance is not implied by aggregate single-trial outcomes (speed and accuracy) which, in turn, are not implied by the structure of motor variability (1/*f* scaling and entropy). Changes in long-range dynamics contingent on a trade-off between speed and accuracy would complete an evaluation of performance at the three different measurement scales.

Half of the participants were presented with a difficult Fitts task (D = 24 cm, W = 0.4 cm). This difficult condition was designed to be incompatible with the speed-accuracy task instruction. We expected that in the presence of incompatible task constraints (i.e., performing a highly precision-constrained task simultaneously fast and accurate), participants would predominantly emphasize one of the conflicting task dimensions over the other, because it is known that participants self-define their position along the continuum of speed versus accuracy while being equally instructed to move as fast and as accurately as possible (cf. Adam, 1992; Rinkenauer, Osman, Ulrich, Mûller-Gethmann, & Mattes, 2004). We exploited the resultant between-subject variability to evaluate whether these performance modes entail constraints that apply to the other two scales of description.

If levels of performance are coupled across timescales, it is expected that movement kinematics and long-range dynamics will be contingent upon control over the emphasized side of the trade-off. For instance, it is known that faster, less accurate performance better capitalizes on the elastic properties of the body, and thus producing more harmonic

kinematics compared with more accurate, but slower performance (e.g., see Figure 4). Equally, there is evidence suggesting that long-range dynamics of human performance are contingent on the emphasized performance mode. For instance, extensive practice of a challenging Fitts task not only leads to faster movement times, but also to clearer 1/*f* scaling and reduced entropy in a time series of movement times (Wijnants et al., 2009). So, if 1/*f* scaling indeed serves as a coordinative basis for goal-directed behavior, the straight-forward prediction follows that clearer 1/*f* scaling, and lower entropy are expected in long-range dynamics pertaining to the emphasized performance outcome (either speed or accuracy). This would entail functional motor synergies optimizing speed and yielding clearer examples of 1/*f* scaling and reduced entropy in *movement time* series. At the same time, a faster performance mode entails less control over accuracy, and thus, less clear examples of 1/*f* scaling and higher entropy are expected in *movement amplitude* series. Conversely, when control comes down on the accuracy side of the trade-off, we may expect clearer examples of 1/*f* scaling and reduced entropy in movement amplitude series, but more random dynamics in movement time series. This would then amount to a trade-off in long-range dynamics that is contingent on the speed-accuracy trade-off.

The other half of the participants was presented with an easy Fitts task (D = 8 cm, W = 2 cm), designed to be compatible with the speed-accuracy task instruction. The targets were five times as large and three times closer together compared to the difficult condition. This easy condition allowed participants to be simultaneously fast and accurate, rather than requiring them to emphasize one task requirement over the other like in a speed-accuracy trade-off. Thus, we expected participants to assemble functional synergies supporting fast and accurate performance simultaneously. Consequently, we anticipate the trade-off between long-range dynamics of movement time series and movement amplitude series, hypothesized in the difficult condition, to be absent in the easy condition because both task requirements can be met simultaneously.

2. Method

2.1 Participants

Thirty undergraduate students were randomly assigned to one of the two difficulty conditions. The participants received course credits for participation. All participants had normal or corrected to normal vision and were right-handed. None suffered from any known motor impairment.

2.2 Materials

Fitts' law allowed us to construct material conditions that differed reliably, and to a known degree, in difficulty. An Index of Difficulty (*ID*, measured in bits/s) has been derived from Fitts' law, using the ratio between the width W of targets and their distance D. For this study, two levels of difficulty were constructed. The difficult condition used circular targets 0.4 cm wide and 24 cm apart, yielding an *ID* of 6.9. At this level of task difficulty, participants are generally unable to produce optimal kinematics and remain accurate, as opposed to the easy condition which used circular targets 2 cm wide and only 8 cm apart, yielding an *ID* of 3 (Guiard, 1993; Mottet & Bootsma, 1999). Movement coordinates were recorded on a WACOM digitizer tablet with a sampling rate of 171 Hz. The input device was an inkless stylus used on a model sheet (A4) placed on top of the digitizer tablet.

2.3 Procedure

Participants were seated on a height-adjustable chair and instructed to use their dominant hand to draw lines (hence, not tapping) back and forth between two circular targets, as quickly and accurately as possible. The targets were positioned one on the left and one on the right side of a printed sheet of paper. When 1100 trials were completed a tone signaled the end of the experiment.

2.4 Data Analysis

We analyzed the participants' performances at three different scales of analysis. From each participants' sequence of 1100 movements we computed an Index of Harmonicity (*H*) from the movement kinematics, aggregate speed and accuracy measures of single-trial outcomes, and long-range dynamics of movement time and movement amplitude series using fractal dimension and sample entropy statistics (as explained below). Then, within each task condition, the 15 participants were ranked on each of the variables applying non-parametric (Spearman) correlation statistics to assess contingencies in the between-subject variability across these variables. We used Spearman's *rho* because we expected monotonic relations, but not necessarily linear ones.

Harmonicity. A measurement called Index of Harmonicity (*H;* cf. Guiard, 1993) was computed based on the acceleration trace of the back-and-forth movements. First, the recorded position time series were filtered using a third-order 5 Hz low-pass Butterworth filter. As a second step the position recordings were rescaled so that the point of zero position was exactly in the middle of the two targets. For example in the easy task condition target distance was 8 cm, so the left target was at -4 cm and the right target at 4 cm.

Then the acceleration time series were computed (in cm/s^2), and segmented so that each segment ranged from one zero-crossing in displacement (movement midpoint) to the next zero-crossing and thus contained one movement reversal. Figure 4a shows three example acceleration profiles segmented this way. The oscillation midpoints are shown as vertical lines, and time is on the x-axis. Also displacement is shown, but note that acceleration and displacement were normalized to bring them on a comparable scale in the figure. Also note that a segment containing a reversal at the right target (positive displacement) is shown as negative acceleration, and a segment containing a movement reversal at the left target (negative displacement) as positive acceleration.

Next, the local extrema (LE) were identified in the acceleration trace of each segment. The minimal and maximal LE within each segment are shown as square markers in Figure 4. *H* was computed as the ratio of the maximal LE to the minimal LE of acceleration for positive displacement (i.e., movement to the right; note, negative acceleration), and vice versa as the ratio of minimal LE to maximal LE for negative displacement (i.e., movement to the left; note, positive acceleration). By construction, *H* ranges between 0 and 1. That is, if acceleration changes sign at a movement reversal (i.e., a corrective movement), *H* is set to 0, reflecting the full dissipation of mechanical energy. The value of *H* was computed for every segment, and averaged to yield a global estimate of *H*.

The extent to which, at movement reversals, terminal braking and initial re-acceleration fuse, as expressed by *H*, is of interest because such a fusion reflects the saving of mechanical energy, that is, the recycling of kinetic energy in potential form. For instance, Figure 4a is taken from the difficult task condition and shows that terminal braking is required when

approaching the target to comply with the high precision constraint, and consequently mechanical energy is dissipated (cf. Figure 2f). In the next movement, re-acceleration is required to meet up with the speed-constraint. This can be seen as biphasic acceleration segments (Figure 4a) of which *H* expresses the depth of the well, hence the amount of mechanical energy that is dissipated. The stronger the deceleration (and the consequent re-acceleration) near movement reversals, the more energy is dissipated and the lower the value of *H*.

In easy task conditions, however, the two peaks in the biphasic acceleration profile tend to merge into a single event (see Figure 4b). The acceleration profile becomes sinusoidal, because the displacement series is perfectly sinusoidal, as in a frictionless mass-spring system. In this case only one LE is detected, and *H* is the ratio of the LE to itself (i.e., $H = 1$), evidencing perfectly simple harmonious kinematics (cf., Figure 2e).

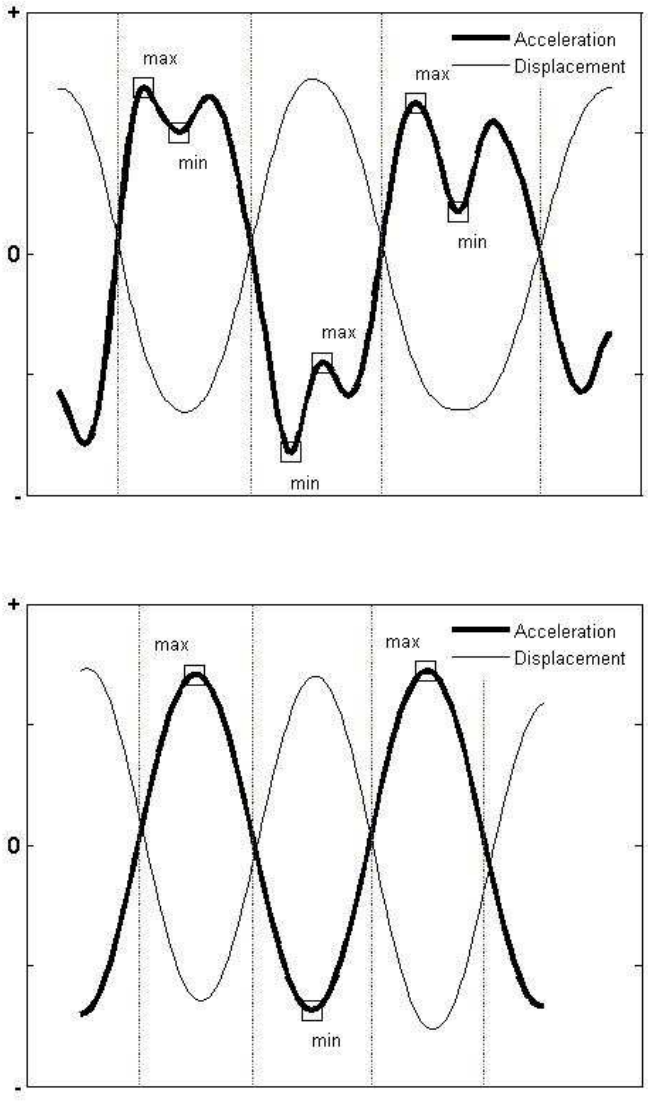

Figure 4. The upper panel shows the normalized acceleration and displacement series observed in 4 half-cycles of movement (difficult condition) divided into three segments, each containing a movement reversal. The minimal and maximal local extrema in each segment are shown as square markers. *H* was computed as the ratio of these extrema (see text). If only one local extreme was observed, as in the lower panel (easy condition), *H* is the ratio of that extreme against itself ($H = 1$).

Speed and accuracy. For each participant, we computed the average movement time and the percentage of accuracy. Movement time (in seconds) was determined as the difference in the number of sampled points between begin and end points of each movement (zero-crossings in velocity), divided by sample rate (in Hz). Accuracy was determined as the percentage of hits (hits/total number of movements*100).

1/f scaling. The repeated performances of each participant were treated as a time series. That is, the movement time and movement amplitude sequences were kept in the trial-order in which they were collected. The movement amplitudes were computed as the one-dimensional distance between zero-crossings in velocity (cf. Fitts, 1954), see for instance Figure 2c and d. We estimated the fractal dimensions of the time series using spectral analysis, standardized dispersion analysis, and detrended fluctuation analysis. These methods are complementary in that the strengths of each compensate for the weaknesses of the others. For instance, spectral analysis, while robust in many respects, requires preprocessing of the signal because extreme observations can contaminate the outcome of the analysis (see Holden, 2005). Detrended fluctuation analysis can be applied to nonstationary signals and is not susceptible to most statistical artifacts or long-term trends, but it can falsely classify certain types of signals as fractal (Rangarajan & Ding, 2000). Standardized dispersion analysis is also highly reliable, but linear and quadratic trends may bias its output. We ensure reliable conclusions by using all three methods together.

With these analyses it is prudent to preprocess the raw data in order to avoid the known pitfalls (Holden, 2005). Therefore, outliers were removed if they lay outside three standard deviations from the mean. Then, linear trends and quadratic trends were removed and the remaining data were truncated to 1024 movement trials, because spectral analysis and standardized dispersion analysis require series lengths that are a power of 2. As a last step, the time series were normalized.

Spectral analysis. Spectral analysis transforms data series from the time domain (e.g., milliseconds) into a frequency domain (Hz), through a Fast-Fourier-Transformation. The procedure finds the best-fitting sum of harmonic sine waves in a data signal, and renders their power (amplitude^2) at each fitted frequency on log-log scales. The total number of estimated frequencies in the Fast-Fourier Transform was 512. The statistic of interest is the slope of the spectral portrait, which captures the relation between amplitudes and frequencies of variation in the data signal. Here, we fitted the spectral slope over the 25% of lowest frequencies (cf. Eke, Hermán, Kocsis, & Kozak, 2002). A zero slope indicates a random signal, a slope of -1 indicates 1/*f* scaling. Spectral slopes as steep as -2 indicate fractional Brownian motion, the epitome of random walk processes (see Figure 3).

Standardized Dispersion Analysis. Standardized Dispersion Analysis (SDA) investigates the scaling of variability with changes in sample size. That is, variability is measured using the standard deviation (using the population formula, i.e., using *N*, the number of data points, in the calculation, rather than the usual bias corrected $N - 1$) of means of progressively larger adjacent samples in a time series. That is, the analysis tracks how dispersion in sample means decreases as progressively larger samples of adjacent data points (bins) are aggregated together in a sample mean. As a first step, the standard deviation is computed for the original data series, which contains 1024 'mean' values of the data points themselves. The second step involves calculating the standard deviation of the 512 means (bins) of each two consecutive measurements (bin size), and so on. We iterated this procedure until only 32 bins were

remaining, each of which represents the mean of 32 adjacent samples in the original time series.

The results from SDA can be seen in a plot of the logarithm of the bin size against the logarithm of the standard deviation, as in Figure 5. For random, white noise, it should not matter that adjacent samples are being grouped and regrouped to form samples of different sizes; for white noise, the slope in Figure 5 is close to -0.5 (see Van Orden et al., 2003, for a detailed description). The outcome of standardized dispersion analysis is expressed by the fractal dimension (*FD*) of a time series, which is given as 1 – the slope of the regression line. Thus, the *FD* of white noise is 1.5. This can be derived simply from the equation for the standard error of the mean ($SE = SD/\sqrt{N}$). For a large sample size *N*, the standard error *SE* gets close to zero, and thus yields a stable population parameter for white noise. Thus, *SE* scales as a function of sample size *N* as $1/\sqrt{N}$ for a *SD* of 1 as in our normalized series. On log-log scales, this can be written as log (*SE*) = -0.5 log(*N*). The slope of -0.5 in Figure 5 simply follows from this equation, and leads to a corresponding *FD* of 1-(-0.5) = 1.5. A shallower slope (i.e., the 1/*f* scaling pattern shown in Figure 5 has a slope of around -0.2; i.e. *FD* equals roughly 1.2), however, indicates correlated activity across timescales, as expressed by the change in a variance statistic due to changes in bin sample sizes. A *FD* thus expresses whether the variance statistic converges fast enough, as sample size increases, to yield a stable population parameter. If not, then the process that produced the variance would reveal a slope that is less steep than -0.5 (suggesting a *FD* less than 1.5), which would indicate a lack of characteristic scale or quantity of variance in the series. An in-depth tutorial of both spectral analysis and standardized dispersion analysis can be found in Holden (2005).

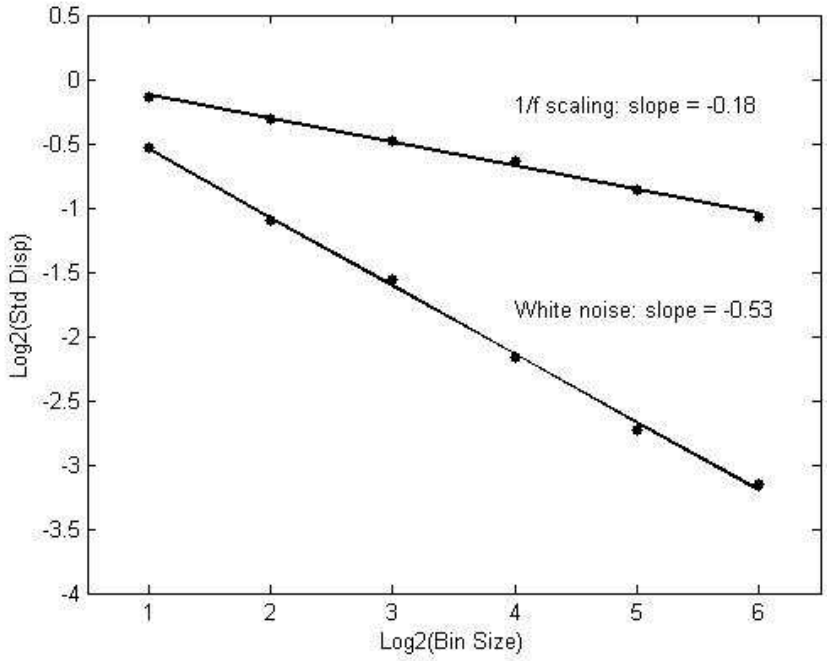

Figure 5. Standardized dispersion is shown as a function of sample-bin size, on log-scales (base 2 was used here). The solid line is the least-squares regression for the six different estimates. Fractal dimension is computed as 1- the slope. The fractal dimension of white noise equals 1.5, whereas a fractal dimension of 1.2 indicates exact 1/*f* scaling.

Detrended Fluctuation Analysis. Detrended Fluctuation Analysis (DFA; Peng et al., 1993) is yet another method to reveal the extent of 1/*f* scaling in behavioral time series, and is especially useful when confronted with nonstationary signals. The first step is to integrate the time series to be analyzed. Next, the integrated time series is divided into bins of equal length, containing *n* data points. In each bin of length *n*, a least squares line is fit to the data (representing the *trend* in that bin). And then the time series is detrended by substracting the local trend in each bin. From the now integrated and detrended time series, the root-mean-square fluctuation (average fluctuation) is calculated. This computation is repeated over various timescales (bin sizes) to characterize the average fluctuation at each timescale. In the present study, DFA was performed on bin sizes ranging between 2^2 and 2^9 data points (ranging from a few seconds to minutes of performance). The results from DFA are usually shown in a plot of bin size against fluctuation, as in Figure 6, in which the scaling exponent is given by the slope. For 1/*f* scaling, fluctuation will increase with bin size, as indicated by a linear relationship on log scales (yielding a slope of 1). White noise yields a slope of 0.5.

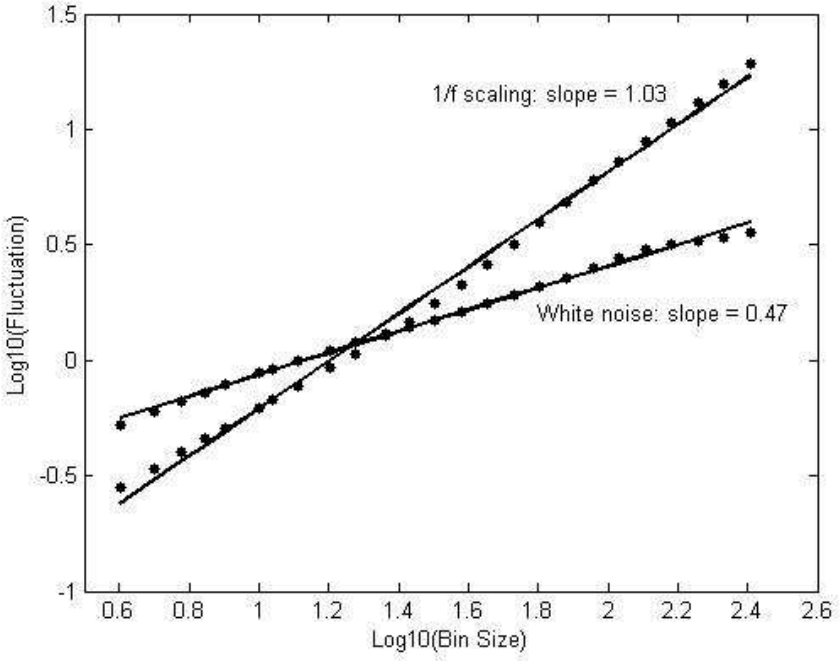

Figure 6. Average fluctuation is depicted as a function of sample-bin size, on log-scales. The solid line is the least-squares regression across timescales. The slope of the regression line equals 0.5 for white noise, and 1 for 1/*f* scaling.

A common scale of Fractal Dimension. The reported fractal dimension statistics were taken from an average of the fractal dimensions across the three estimates (spectral analysis, SDA, and DFA). The outcomes of spectral analyses and DFA were first transformed into a common scale of fractal dimension. We assumed that a fractal dimension of 1.5 equals white noise, exact 1/*f* scaling yields a fractal dimension of 1.2, and Brownian motion 1.1, and then fitted a curve between these values and the desired corresponding spectral slope (i.e., white noise = 0, pink = -1, and Brownian motion = -2) and DFA exponents (i.e., white noise = 0.5, pink = 1, and Brownian motion = 1.5). This led for spectral analysis to the conversion formula $FD = (\alpha^2 + 4\alpha + 15) / 10$, where *FD* is the fractal dimension, and α the slope of the power spectrum, and for DFA, $FD = 0.4\beta^2 - 1.2\beta + 2$, where β is the slope of the log-plot of bin size against fluctuation. For a more in-depth discussion on conversion strategies, see Hasselman (2012).

Sample Entropy. We supplemented the fractal analyses by estimating the entropy in each data series. Entropy measures have previously been used as a gauge of complexity in human performance (e.g. Newell, Broderick, Deutsch, & Slifkin, 2003; Slifkin & Newell, 1998; Stergiou & Decker, 2011) and covary with fractal statistics in goal-directed movements (Wijnants et al., 2009). The measure of entropy used here is called Sample Entropy or SampEn. SampEn (*m*, *r*, *N*) is the negative natural logarithm of the conditional probability that a data set of length *N*, having stayed within a tolerance *r* for a number *m* of data points, will continue within that tolerance at the next point, disallowing self-matches. SampEn can thus be considered a measure of self-similarity in a time series and was computed as described by Richman and Moorman (2000).

Sample entropy measures generally range between 0 and 2, where higher values indicate more uniform dispersion of data values (less structured). Our results were robust over a wide range of choices for *m* and *r*. In the present analysis, we used parameter values of $m = 3$ and a tolerance of $r = 1$ *SD*, which were both comfortably within that robust range. Sample entropy has the advantage over approximate entropy because it is less biased (i.e., the procedure does not include self-matches), and more robust over a range of input parameters (see Lake, Richman, Griffin, & Moorman, 2002).

3. Results

3.1 Descriptive statistics

The means and standard deviations pertaining to each of the measured variables are presented in Table 1 for both task conditions. As expected, participants in the difficult condition produced slower and less accurate movements than participants in the easy task condition. In the difficult condition, participants also produced less harmonic oscillating behavior, as expected given the conflicting speed-accuracy constraints involved. The sample entropy of movement amplitude series was higher in the easy condition, which is likely an artifact of the larger movement amplitude tolerance in the easy condition.

Table 1.
Means and Standard Deviations of the Measured Variables in the Difficult and Easy Condition.

	Task Condition		
	DIFFICULT	*EASY*	*t*(28)
Harmonicity (SD)	.40 (.16)	.96 (.05)	-13.32**
Movement Time (SD)	655 *ms* (117)	201 *ms* (66)	13.04**
Accuracy (SD)	32.4 % (18.2)	78.1 % (25.4)	-5.66**
Fractal Dimension MT (SD)	1.28 (.08)	1.23 (.09)	1.60
Fractal Dimension MA (SD)	1.33 (.12)	1.29 (.07)	1.17
Sample Entropy MT (SD)	.49 (.13)	.41 (.15)	1.53
Sample Entropy MA (SD)	.37 (.11)	.51 (.12)	-3.37**

** $p < .01$.

3.2 Non-parametric correlations

We used one-tailed Spearman correlations to relate the 15 pairs (individual participant scores) of each combination of the measured variables in both task conditions. This implies separately

ranking the individual values within and across their scale of observation. We first discuss the contingencies among variables within each scale of performance, before proceeding to the vertical couplings among the levels themselves.

Within scales of performance. Within the observational level of single movement outcomes, the speed and accuracy measures traded off reliably between-subjects in the difficult condition (movement time and hit rate were positively correlated, $\rho = .84$, $p < 0.01$). In the easy task condition, however, no speed-accuracy trade-off was observed between-subjects ($\rho = -.10$, $p = 0.36$). Intriguingly, the manipulation of task difficulty had the same effect on the observed long-range dynamics. In the difficult condition, temporal (movement times) and spatial (movement amplitude) sources of 1/*f* scaling traded off reliably ($\rho = -.64$, $p < 0.01$), as did the entropy values ($\rho = -.84$, $p < 0.01$).

In the easy task condition, however, no trade-offs were observed between spatial and temporal streams of 1/*f* scaling. To the contrary, the fractal dimensions of movement time vs. movement amplitude were positively correlated ($\rho = .63$, $p < 0.01$), indicating that participants who exploited a wider range of scale-free variability in their temporal performance, also showed clearer fractal-like patterns of variability in their spatial performance. This win-win vs. loose-loose situation was not reliably countered by measures of sample entropy, however ($\rho = .40$, $p = 0.07$).

Across scales of performance. From the previous paragraph it remains to be answered how our finest scale of observation (movement kinematics) fits into the equation. This question, however, pertains to contingencies across timescales because the harmonicity index primarily reflects the trade-off of energy dissipation of the moving arm against the imposed speed and accuracy constraints, rather than a pure ‘within-timescale’ trade-off.

As expected, the Index of Harmonicity (*H*) was contingent upon the balance of speed and accuracy in the difficult condition. In the difficult condition, participants that showed shorter movement times produced higher values of *H* ($\rho = -.90$, $p < 0.01$), and vice versa, slower participants showed less harmonic movements. More surprisingly, *H* was equally contingent on the observed long-range dynamics (see Table 2). Clearer harmonic motion in participants’ back-and-forth oscillations went with clearer 1/*f* scaling in movement times (Fractal Dimension of Movement Time ranged from 1.14 to 1.42), but with less clear 1/*f* scaling in movement amplitudes (Fractal Dimension of Movement Amplitude ranged from 1.12 to 1.52). Vice versa, less harmonic performances yielded less clear 1/*f* scaling in movement times, but clearer 1/*f* scaling in movement amplitude. These fairly strong relations were confirmed by the entropy measures at every turn. In the easy condition, in contrast, none of these relations were reliable.

Given the former results, it comes as no surprise that speed and accuracy themselves are closely tied to the long-range dynamics observed in goal-directed behavior. That is, in the difficult condition, faster participants showed more 1/*f* scaling in the movement time series (the positive relation indicates that low values of Movement Time are associated with low values of Fractal Dimension of Movement Time), and less 1/*f* scaling in their movement amplitude series (the negative relation indicates that low values of Movement Time are associated with high values of Fractal Dimension of Movement Amplitude), while more accurate participants showed less 1/*f* scaling in their movement time series (hence, the positive correlation between accuracy and Fractal Dimension Movement Time), but more 1/*f* scaling in their movement amplitude series (hence, the negative correlation between accuracy

and Fractal Dimension Movement Amplitude), as shown in Table 2. Also these relations were confirmed by the sample entropy measures. And most importantly, each of these relations was absent in the easy condition.

Table 2.
For Both Task Conditions, Spearman's rho is Shown for the Vertical Couplings (Across Timescales) Between the Measured Variables; Harmonicity at the Finest Timescale, Movement Time and Accuracy at the Aggregate Level of Whole Movements, and Fractal Dimension (FD) and Sample Entropy (SampEn) of the Slower Timescales, Found in Movement Time (MT) and Movement Amplitude (MA) Series.

		Harmonicity	Movement Time	Accuracy
Difficult Condition	FD MT	-.61**	.52*	.70**
	SampEn MT	-.66**	.45*	.74**
	FD MA	.50*	-.45*	-.48*
	SampEn MA	.75**	.-.64**	-.74**
Easy Condition	FD MT	-.13	.00	.15
	SampEn MT	-.12	.03	.05
	FD MA	-.31	.33	.30
	SampEn MA	.03	-.08	.33

** p <.01, * p <.05, one-tailed.

4. General Discussion

The present experiment builds upon a long line of research addressing the relation between movement speed and accuracy in goal-directed movements, the kinematics of the movement trajectory itself, and their mutual relation. It was designed to replicate the relation between Fitts' law (Fitts, 1954) and Hooke's law (Hooke, 1678) and to extend this coupling to another lawful physical phenomenon: the presence of fractal dynamics in the behavior of complex, biological systems (Bak, Tang, & Wiesenfeld, 1987; Mandelbrot, 1982). Our hypothesis was that control over goal-directed movements is not to be found at a single isolated level within an individual's functional architecture, but rather in an emergent, dynamic fashion out of the ongoing interaction between processes taking place at multiple scales simultaneously.

We investigated a perceptual-motor task at three different scales of measurement (movement kinematics, movement time and accuracy, and long-range dynamics) to inspect possible linkages within and between these performance scales. Half of the participants were presented with a challenging task condition that was designed to yield incompatible speed-accuracy constraints, so that more accurate participants would be slower performers and faster participants less accurate performers. With the challenging constraints imposed, as expected, faster participants produced more harmonic oscillations than more accurate but slower participants. These measures (harmonicity, revealing details about within-movement kinematics, and movement time and accuracy, revealing the outcomes of whole movements), each at their own scale of observation, were tightly coupled with the long-range dynamics of movement times and movement amplitudes. This third scale of observation pertained to a measurement window ranging from less than a second up to minutes of performance.

In the difficult task condition a close coupling was revealed among measured values probing the different scales of performance. Participants who predominantly emphasized speed,

showed more harmonic limb oscillations and clearer 1/*f* scaling in their produced movement time series (but more random spatial long-range dynamics). More accurate participants, in contrast, showed less harmonicity and clearer 1/*f* scaling in their produced movement amplitude series (but more random temporal long-range dynamics). A clearer presence of 1/*f* scaling thus hinges on the task requirement emphasized by the participant. This pattern of couplings among embodied timescales was accompanied by a trade-off between the long-range dynamics of movement time and movement amplitude that was contingent upon the speed-accuracy trade-off. Corresponding sample entropy statistics paralleled the correlations with fractal statistics at every turn.

The observed cross-scale dependencies within an individual's performance confirmed our initial suspicion that task-specific constraints affect performance measures regardless of the scales of performance to which they pertain. When faced with incompatible task requirements, the predominant performance mode of the participants (either the speed or the accuracy side of the trade-off) was equally expressed by movement kinematics, average speed and accuracy, and spatial and temporal long-range dynamics. This suggests that near the limits of coordination, human performance has the tendency to only use only a narrow set of solutions, specific to the emphasized task requirement, and regardless of measurement scale, more autonomy (a wider set of solutions) is sacrificed to gain control. The source of consistent trade-offs at different measurement scales may simply be that these solutions are distributed across the measurement scales of embodied constraints, rather than within a particular scale.

None of the systematic relations found in the difficult condition were reliable in the contrasted easy condition, however. For instance, the lack of trade-off in the aggregate speed and accuracy measures was absent in the corresponding long-range dynamics (actually conversed in the easy condition). The lack of systematic relations among the different measurement scales in the easy condition is likely a consequence of the restriction of range within the measured variables, since harmonicity, speed, and accuracy were all dispersed relatively close to their ceiling values in the easy condition.

It is not unconceivable, however, that, under these less stringent constraints, human performance becomes more flexibly organized as synergies that can be formed over a wider range of degrees of freedom, what Gelfand and Latash (1998) called the *principle of abundance*. Abundant controllable degrees of freedom make it possible to be fast and accurate at the same time in easy conditions, which would also yield performances close to their ceiling values. For instance, in face of compatible speed-accuracy constraints, harmonious oscillations can energetically self-sustain themselves by exploiting the elasticity of the muscles and the joints. Consequently there is little need for the kinematics to be so tightly constrained by the other requirements of task performance. The cross-scale coupling among these factors is thus hidden by the fluid ease and skill with which performance is enacted. Hence, the fluid accommodation of the task masks the nature of the coupling across scales by which it is accomplished, and in this respect the conflict between task constraints of speed and accuracy provided a means to test this hypothesis.

The observation that a restricted dispersion of measurement values reduces or even masks the relations between long-range dynamics and other performance measures is consistent with other studies (e.g., Torre & Balasubramaniam, 2011; Wijnants et al., submitted). These observations do not imply, however, that every timescale is controlled separately in more manageable task settings. By contrast, it is conceivable that at the limits of a behavior where errors and other qualitative changes can be observed, a complex system simply reveals itself

in most detail (e.g., Kelso, 2003). That said, we do not want to rule out the possibility that another set of observables with a less restricted data range could be defined in easy conditions that would still exhibit rich cross-scale relationships.

The close coupling of performance outcomes observed in the difficult condition (either serving the speed or the accuracy side of the trade-off) enabled for improved performance along the emphasized task requirement; at the cost of loosing control over the other, however. The fact that this was paralleled by clearer 1/*f* scaling in the variable that pertained to that task requirement suggests that interdependent timescales mutually constrain their respective degrees of freedom, rather than that every scale is controlled separately. This illustrates how system components may interact so completely that one can no longer parse their individual contributions in the collective activity of the whole. While performance at each measurement scale may contribute its own potentials and constraints in shaping this collective activity, the activity at each scale is strongly interdependent with the activities at other scales.

Based on traditional approaches in the Fitts paradigm, observing 1/*f* scaling and consistent changes in its presence may run against standard intuitions, and certainly when it is tied so strongly to other functional variables of a performance, because trial to trial performances are typically assumed to fluctuate randomly from trial to trial. The assumption that movement variability is a product of unstructured, white neuromotor noise superimposed on a deterministic signal traces back to Fitts and was built on the tenets of information theory (Shannon, 1949), which treats variability as random 'errors', which to some extent contaminate an underlying deterministic (average) signal in the information processing stream (Broadbent, 1958, Fitts, 1954). As a consequence, standard approaches to the speed-accuracy trade-off are often limited to an exchange rate for the disparate units of speed and accuracy at their fixed measurement scale (i.e., without making predictions about movement trajectories).

In the 60s and 70s of the 20th century, motor control theorists began to adopt the language of control theory to account for the specificities of the trajectories themselves. As one example, Meyer's optimal control model (Meyer, Abrams, Kornblum, Wright, & Smith, 1988) captured movement variability as a function of the velocity of sub-movements, thereby extending the relevant scales of analysis in a speed-accuracy trade-off to movement kinematics. Substantial theoretical developments have followed (For a review, see e.g. Elliot, Hansen, Mendoza, & Tremblay, 2004; MacKenzie, 1992; Plamondon & Alimi, 1997), leading eventually to the recognition that a trial movement time can be modeled from the kinematics as an emergent property (e.g., Bootsma, Mottet, & Zaal, 1998; Bootsma, Fernandez, & Mottet, 2004).

Our main message is that a second round of progress in the Fitts paradigm is apt, which steps beyond identifying causal relations between movement kinematics and movement durations, by accepting the challenges imposed by fractal scaling and spontaneous entropy reduction in well-coordinated performances. Gauging 1/*f* scaling and entropy extends beyond the usual scales of analysis, and reveals nonetheless cognitive structure that was previously hidden, but equally sustains (and is constrained by) a given task performance and a participants' emphasis therein. So, while the observed relation between kinematics vs. speed and accuracy is not new, our study clearly builds upon the long history of research in the Fitts paradigm by adding the measurement scale of long-range dynamics. The consistent changes in 1/*f* scaling in different task performances suggest that it is far too simplistic for kinematic features at their fast timescale, defined by a task condition, to 'cause' a corresponding average movement time and movement amplitude at a coarser scale, because basic features of a performance cannot

simply be averaged out to obtain unicausal features at longer time scales (i.e., up to long-range dynamics).

That is, far from being a statistical or functional nuisance, a consistent coupling of scales appears to be a signature of strongly emergent coordination (cf., Buzsaki, 2006; Diniz et al., 2011; Kello et al., 2007; Van Orden et al., 2003). Emergent coordination allows slower timescale dynamics to supply specific constraints on the possible changes at faster timescales. Faster timescales in turn can act as intermittent sources of perturbations and change to the slower timescale dynamics (if they are amplified in positive feedback), which amounts to a circular, nested, or downward influences among timescales of constraint. The result is emergent and system-wide control that is economical in the sense that it reduces the number of variables that must be independently specified in the coordination of a given performance (Turvey, 2007; Van Orden et al., 2003; Wijnants et al., 2009).

The observation that a constituent part of a performance constrains the efficient functioning of the same system's other parts through cross-scale contingencies raises the broader question of fractal dynamics in human control. The specific meaning of $1/f$ scaling that we have hypothesized refers in itself to activity across interlinked timescales. Here we accompanied this statistical regularity with actual empirical cross-scale observables that pertain to intra-individual modes of coordination to satisfy task demands. Previous widespread findings associate change in scaling exponents, in the direction of $\alpha = 1$ of $1/f$ scaling, with fluid task performance (e.g., Diniz et al., 2011; Goldberger et al., 2002; Kello et al., 2007; Van Orden et al., 2011; Werner, 2010; Wijnants, 2012). The present findings add to these observations and suggest that control is delegated across interdependent embodied scales that exploit the natural constraints imposed on peripheral muscle systems (i.e., springlike properties) as well as emergent patterns of coordination (i.e., $1/f$ scaling), to situate task performance within the particular demands of task contexts.

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Chapter 4

An interaction-dominant perspective on reading fluency

Based on:

Wijnants, M. L., Hasselman, F., Cox, R. F. A., Bosman, A. M. T., & Van Orden, G. (2012). An interaction-dominant perspective on reading fluency and dyslexia. *Annals of Dyslexia, 62*, 100-119. doi: 10.1007/s11881-012-0067-3

Abstract

CHAPTER 4

The background noise of response times is often overlooked in scientific inquiries of cognitive performances. However, it is becoming widely acknowledged in psychology, medicine, physiology, physics, and beyond that temporal patterns of variability constitute a rich source of information. Here, we introduce two complexity measures (1/*f* scaling and Recurrence Quantification Analysis) that employ background noise, as metrics of reading fluency. These measures gauge the extent of interdependence across, rather than within cognitive components. In this study, we investigated dyslexic and non-dyslexic word-naming performance in beginning readers and observed that these complexity metrics differentiate reliably between dyslexic and average response times, and correlate strongly with the severity of the reading impairment. The direction of change in the introduced metrics suggests that developmental dyslexia resides from dynamical instabilities in the coordination among the many components necessary to read, which could explain why dyslexic readers score below average on so many distinct tasks and modalities.

1. Introduction

When learning to read, young children must develop stable, yet flexible, relations among graphemes and phonemes. Reading fluently means coordinating these often inconsistent relations with the perceptual and motor processes necessary to read. A failure to achieve such flexible stability or coordination thus results in a failure to read fluently (see Bosman, Vonk, & van Zwam, 2006). For instance, developmental dyslexia results in slow and/or inaccurate reading performance. But the possible cause of developmental dyslexia is still much debated after decades of intensive research, however.

One factor that troubles the search for single causes of dyslexia is the long list of criteria that is held to differentiate among dyslexic and average readers. For instance, dyslexic readers have been found to score below average on perceptual, motor and cognitive skills pertaining to speech and language, working memory, attention, ordering and sequencing, temporal processing, balance and motor control, auditory and tactile processing, mental calculations, and much more (e.g. Elliot & Gibbs, 2008). Moreover, it appears that neither of those criteria by themselves is essential for diagnosis, nor specific to developmental dyslexia (e.g. Ramus, 2003). In fact, neither phonological awareness nor biological factors alone can provide a full account for the plethora of empirical findings (e.g., Blomert & Willems, 2010; Snowling, 2008; Torgesen, 2007). And in neuroscience, equally, a bewildering range of anatomical differences is held to differentiate between children with developmental dyslexia and average readers. These include reductions in temporal lobe, frontal lobe, caudate, thalamus and cerebellum (Brown et al., 2001), insula, anterior superior neocortex, posterior cortex (Pennington, 1999), occipital cortex (Eckert et al., 2003), and a relative increases in the size of temporal and parietal plana (Green et al., 1999).

The observation that so many different processes or components may contribute to the learning disability constitutes an interesting observation in itself, which poses specific challenges to any theory of developmental dyslexia (Démonet, Taylor, & Chaix, 2004; Hasselman, 2012, pp. 29-31; Ramus, 2003). Dealing with this plentitude of possibly deficient components is not trivial, especially since many effects appear to be extremely context-specific from time to time (Blomert, & Mitterer, 2004; Holden, Choi, Amazeen, & Van Orden, 2011; Manis, & Keating, 2005; Ramus & Szenkovits, 2008; Van Orden, Holden, Podgornik, & Aitchison, 1999). If one additionally considers the variety of brain regions implicated in dyslexia (e.g., Leonard, Eckert, Given, Virginia, & Eden, 2006), it becomes even more

difficult, if not impossible, to pinpoint a single deficient region or component of the brain whose malfunctioning uniquely leads to developmental dyslexia. Therefore, some authors have questioned whether there is in fact one isolable mechanism, deficient in dyslexic reading, which specifically serves the function of decoding written language (Bosman & de Groot, 1996; Elliot & Gibbs, 2008; Van Orden, Pennington, & Stone, 2001).

The idea that there may not be an isolable causal source of developmental dyslexia may perhaps not even be as strange as it may appear. For one, the task of becoming literate is undoubtedly complex, irregular and subservient to other linguistic and cognitive abilities, and therefore arguably a multifaceted process (Wallot & Van Orden 2011a). As an example, learning to read is essentially multi–sensory in nature (Blomert, 2011; Lankhorst, Bosman & Didden, 2008). In addition, around 70 muscles must coordinate to pronounce a single utterance (Turvey, 2007). Successful reading may therefore emerge from a multitude of interdependent processes (e.g., Holden, Van Orden, & Turvey, 2009; Kello & Van Orden, 2009). In fact, in fluent reading the intrinsic dynamics of the components themselves may matter less than the mutual interdependence among those components (Van Orden & Holden, 2002; Rueckl, 2002; Van Orden & Kloos, 2003).

Nonetheless, experimental designs generally aim at comparing the measured variables as treatment cells to expose single, causally potent, sources of variance, as in an ANOVA (i.e., simple cause-and-effect relations). This means that many studies are exposed to infer the workings of the independent components and subcomponents of sensation, perception, reading, and articulation, each representing independent cognitive functions. These components are usually assumed to concatenate their effects like a row of time-ordered falling dominos, each affecting the next in its turn, often spanning several levels of analysis from the biological to the cognitive and behavioral domain (cf. Ramus, 2004). Although the merits of this approach are well-acknowledged, this approach in isolation is limited nonetheless by the inability to reveal structure not contemplated by ANOVAs or other variance component designs (see Gilden, 2001; Van Orden, Holden & Turvey, 2003).

Specifically, experiments designed to reveal independent processing components assign background noise the status of unexplained variance. That is, it is assumed that response series fluctuate randomly around a more or less constant mean. The underlying assumption then is that slower response times indicate a defect in one of the discrete processing operations that additively determine the duration of the response process. However, it is now becoming clear that trial-by-trial variability rarely constitutes white, Gaussian noise. Rather, complex temporal dependencies carry over timescales up to minutes of performance (Gilden, 2001; Riley & Turvey, 2002; Riley & Van Orden, 2005; Van Orden et al., 2003). With this in mind, the present study treats response variability as a trial-ordered response series to evaluate reading performance, and unconventionally, does not concern isolated components of cognitive architecture. The question posed is rather how the essential cognitive activities interact, and become so entangled, to give rise to fluent reading.

With this question in mind, we employed two complexity measures (cf. Wallot & Van Orden, 2011b) to investigate the temporal structure of response variability of dyslexic and non-dyslexic word-naming performance. These metrics, known as 1/*f* scaling and Recurrence Quantification Analysis (RQA) were used to provide a characterization of the dynamical dependencies among the ongoing processes involved in dyslexic and non-dyslexic reading performance. First, we introduce these metrics, and then, we formulate our hypothesis about the nature of developmental dyslexia, based on these metrics.

1.1. 1/f scaling

$1/f^{\alpha}$ scaling presents a phenomenon that is receiving growing interest in psychology and beyond. It is a describing property of the trial-by-trial variability of a time series, and is observed most clearly during repeated human performances when faced with the same task in stable conditions. 1/*f* scaling indicates that the magnitude of variation in response latencies is proportional to the timescale on which it is measured, thus composing a complex sequence effect spanning over the entire time course of an experiment. For a response series which composes random noise, it is fair to assume that cognitive operations are initiated by the stimulus and finish together with the response. As the extent of 1/*f* scaling increases (and hence, departures from randomness), however, this signifies the presence of processes that extend beyond the time boundaries of single trials, and interact across interdependent timescales of performance.

Specifically, 1/*f* scaling of a response time series means that changes in power (the amplitude of changes in response latency over trials) are typically small at the highest frequencies in the time series (i.e., extending over few trials), but that those changes are embedded in overarching, lower frequent changes of higher amplitude (spanning over a larger scale of measurement). 1/*f* scaling thus composes a nested pattern of response variability across scales. This can be seen in a time series plot of 1/*f* fluctuations (i.e., Figure 1c), the series has the same "look and feel" as one zooms in or out to see more fine-grained or coarse-grained features of the fluctuations. It follows that a 1/*f* scaling relation can be expressed as a relation between the size of changes (power), and how often changes of that size occur (frequency), which is inversely proportional on logarithmic scales, see Figure 1d. In contrast, a time series consisting of independent repeated measurements (i.e., white, random, Gaussian noise) does not represent such a relationship (see Figure 1a and b).

Time-evolutionary properties like 1/*f* scaling are essential because they are not visible, and even discarded, in most standard statistical analyses of cognitive performance (Riley & Turvey, 2002; Slifkin & Newell, 1998), while they do effectively distinguish between experimental conditions (e.g., Chen, Ding, & Kelso, 1997; Kello, Beltz, Holden, & Van Orden, 2007; Gilden & Hancock, 2007; Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009). In fact, structured variability (i.e., 1/*f* scaling) appears to be the rule rather than the exception in cognitive performances, and is often as revealing as aggregate information in terms of unpacking the nature of the system organization (e.g., Ihlen & Vereijken, 2010; Hausdorf, 2007; Kello et al., 2007; Van Orden et al., 2003). To date, dozens of studies have been published on long-range dependence in cognitive and motor performance, all demonstrating widespread 1/*f* scaling (e.g., Kello et al., 2007; Van Orden, Kloos, & Wallot, 2010, are reviews). But although 1/*f* scaling has been observed throughout human physiology and behavior, in varying degrees, its origin and meaning remains unclear (Diniz et al., 2011; Van Orden et al., 2003; 2005; Wagenmakers, Farrell, & Ratcliff, 2005).

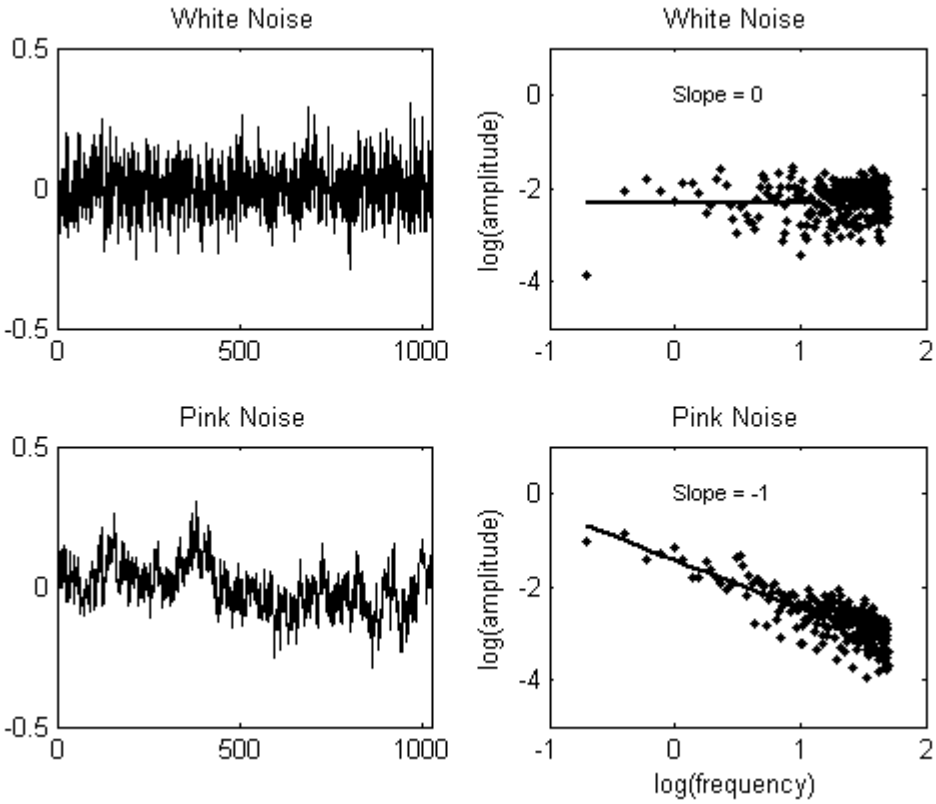

Figure 1a-d. Typical examples of white noise (a) and 1/*f* scaling (c), and their respective power spectra (b and d).

One position in the ongoing debate is that 1/*f* scaling is a typical behavior of self-organizing systems, which reflects a fundamental aspect of all physiological and cognitive functions, which is their emergence in the balance of independent versus interdependent component activities. And in recent years, there has been a growing empirical support for the position that 1/*f* scaling indeed reflects the interaction of many ongoing processes over a multiplicity of interdependent scales, thereby serving as a coordinative basis of cognitive function (e.g. Kello et al., 2007, Van Orden et al., 2011; Wijnants et al., 2009). That is, 1/*f* scaling is usually seen most clearly in well-coordinated behaviors, and less clearly in non-optimal performance or with aging and disease (e.g., Goldberger et al., 2002; West, 2006).

For instance, deviations from 1/*f* scaling (either towards white noise or towards Brownian noise) have been found with epilepsy (Ramon, Holmes, Freeman, McElroy, & Rezvanian, 2008), heart failure (Goldberger et al., 2002), fetal distress syndrome (Goldberger, 1996), major-depressive disorder (Linkenkaer-Hansen et al., 2005), mania (Bahrami, Seyedsadjadi, Babadi, & Noroozian, 2005), attention-deficit-hyperactivity-disorder (Gilden & Hancock, 2007), autism (Lai et al., 2010), Alzheimer's disease (Abásolo, Hornero, Gómez, García, & López, 2006), Huntington's disease (West, 2006), Parkinson's disease (Hausdorff, 2007), and even slow transit constipation (Yan, Yan, Zhang, & Wang, 2008). In each of these studies, healthy controls revealed long-range dynamics reliably closer to 1/*f* scaling.

In addition, the presence of 1/*f* scaling increases with learning (Wijnants et al., 2009) and decreases as task demands increase (Clayton & Frey, 1997; Correll, 2008). The presence of 1/*f* scaling also correlates, for instance, with the severity of depression symptoms (Linkenkaer-Hansen et al., 2005), the success rate of recovery from traumatic brain injury (Burr, Kirkness, & Mitchell, 2008), and falling risk in elderly (Hausdorff, 2007). In each case,

more flexibly stable, adaptive, or coordinated behaviors showed clearer 1/*f* scaling. These many studies together raise the suggestion of close linkages between fractal, 1/*f* scaling dynamics and coordination in human physiology and cognition. With these precedent studies in mind, it is not unlikely that research on learning disabilities like dyslexia may benefit from an assessment of the dynamics underlying impaired reading performance.

1.2. Recurrence Quantification Analysis of response times

RQA is a nonlinear technique to quantify recurring patterns and parameters pertaining to the stability and dimensionality of the underlying dynamics from a time series. Like physicists, physiologists, chemists, biologists, seismologists, physicians, economists, and more, behavioral scientists are usually confronted with systems characterized by a large number of participating, often interacting variables. RQA allows a direct access to such systems by reconstructing, from a single measured variable in the interactive system, a behavior space (or phase-space) that represents the dynamics of the entire system. This reconstruction is achieved by the method of delay-embedding that is based on Takens' theorem (Takens, 1981). The phase space reconstructed from the time series of this single variable informs about the behavior of the entire system because the influence of any interdependent, dynamical variable is contained in the measured signal. The reconstruction itself involves creating time-delayed copies of the time series of a variable that become the surrogate dimensions of a multi-dimensional phase-space. Consequently, the original variable becomes a dimension of the system in question and each time-delayed copy becomes another dimension of the system (Marwan, Romano, Thiel, & Kurths, 2007; Riley & Van Orden, 2005, are tutorials).

The trajectories in this multi-dimensional phase-space represent the system dynamics, and the ensemble of these trajectories is called an attractor, as depicted in Figure 2. RQA quantifies, for instance, whether a data point recurs at another point in time, or whether a sequence of recurring data points forms a recurring pattern of (multiple) neighboring data points in the reconstructed phase-space. The parameters estimated by RQA include *Recurrence Rate* (how many data points recur, or revisit shared locations in phase space, given a certain radius or neighborhood size. Recurrence rate indicates the degree of randomness in the time series, or the confinement of the attractor, *Determinism* (the portion of recurrent measurement values which are parts of a recurring pattern in phase-space), the Shannon *entropy* of the distribution of the lengths of deterministic patterns (entropy indicates the complexity of the attractor), and *meanline* (the average length of deterministic patterns, indicative of the stability of the system). In the Method section, it is explained how each of these measures are computed.

To exemplify what RQA outcomes indicate exactly, consider an attractor reconstructed from a process with a steady mean imposed by random background noise, as typically assumed in reading research. The resulting (high-dimensional) reconstructed phase space would yield little recurrence (neighboring points in phase space), and little or no determinism (recurring patterns of data points) because at most a few of the incidental recurrences would carry over more than one trial. The entropy measure, in RQA, indicates how much "disorder" is there in the duration of recurrent sequences. For a random signal, however, there are little if any differences (very ordered) in the duration of recurrent sequences, which typically all are very short. Therefore a random signal will carry low entropy in the distribution of the durations. Also the value of meanline is small, because the probability of observing a recurrent pattern of a given length in a stochastic signal decreases for each increase in duration. A process consisting of many intertwingled variables, on the other hand, contains a much richer dynamical history. That is, recurrence rate and determinism increase the more a system's

dynamics are dominated by interaction-dominant dynamics. Also, the entropy in the distribution of the duration of deterministic patters is higher in more complex dynamics because more recurrent patterns (determinism), of shorter and longer duration (meanline) are observed than is ordinarily to be expected.

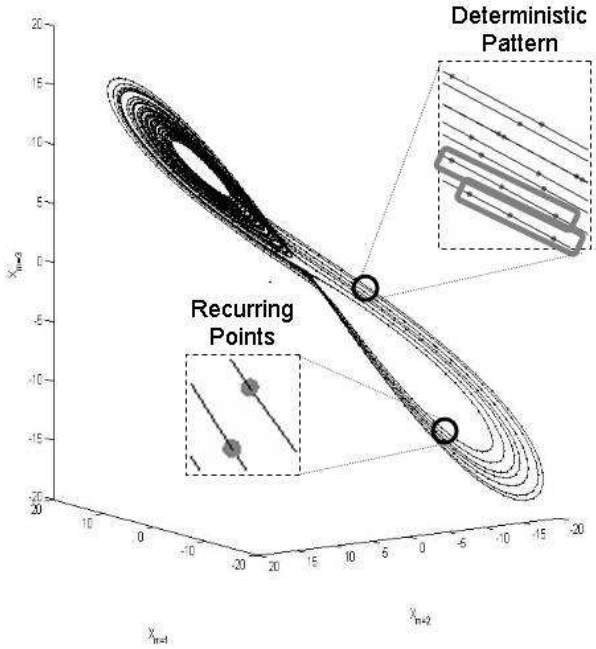

Figure 2. A phase space reconstruction of a highly deterministic system. The insets represent examples of recurrence (points that share common locations in phase space) and determinism (patterns of recurring points).

Over a thousand studies across scientific disciplines have used RQA to study a wide range of complex phenomena (http://www.recurrence-plot.tk/bibliography.php), including neuronal spike trains (Kaluzny & Tarnecki, 1993), breathing rhythms (Webber & Zbilut, 1994), cardiology (Marwan, Wessel, Meyerfeldt, Schirdewan, & Kurths, 2002), protein sequences (Giuliani, Benigni, Sirabella, Zbilut, & Colosimo, 2000; Manetti, Ceruso, Giuliani,Webber, & Zbilut, 1999), electroencephalographic activity (Acharya, Faust, Kannathal, Tjileng Chua, & Laxminarayan, 2005; Marwan & Meinke, 2004; Thomasson, Hoeppner, Webber, & Zbilut, 2001), electromyographic data (Webber, Schmidt, & Walsh, 1995), among other examples. As a statistical method, RQA has thus proven its worth conceptually and mathematically, to reliably and sensitively investigate complex temporal dependencies in systems that contain many interdependent variables, and consequently, emit complex and nonlinear temporal patterns of variation.

1.3. Hypothesis

We compared the word-naming performance of young dyslexic (age 7 to 8) and non-dyslexic (age 6 to 7) readers. The young age of these children together with the task of naming unrelated words offered the advantage of investigating naming fluency at an early stage of

reading development. This allowed us to inquire early signs of developmental dyslexia in the temporal structure of naming latencies, using 1/*f* scaling measures and RQA. As a control group we used the closest possible reading-age match to the dyslexic group.

If successful reading indeed requires multiplicative interactions among cognitive processes, we may expect that in dyslexic word-naming performance the cognitive processes necessary to read show a reduction in the extent of their mutual interactions (cf. Holden, 2002; Holden et al., 2009; Wallot & Van Orden, 2011b). This prediction aligns with the many recent findings across human physiology and cognition that reveal less clear 1/*f* scaling in less coordinated, less fluent processes. Well-coordinated behavior at the other hand possibly emerges from principles akin to self-organization. That is, a system may self-control its behavior so that it becomes governed by low dimensional dynamics that concisely meet the specific task demands at hand.

This entails for instance that, while conventional perspectives presume that different classes of words may require different mechanisms each revealed by distinct time courses (e.g., Coltheart, 1978; Coltheart, Curtis, Atkins, & Haller, 1993), a perspective of interaction-dominant dynamics allows that all response times gauge the selfsame process. Our aim was to investigate whether a more general lack of coordination among processes underlies dyslexic reading performance, than would be suggested if the reading impairment were caused by a single deficient component part of the system.

With this goal in mind, 1/*f* scaling and RQA allowed measuring the relative degree of interdependence among system components. Specifically, we expected dyslexic word-naming latencies to reveal more random, higher-dimensional, less structured, and less complex dynamical signatures, relative to non-dyslexic reading performance. That is, we expected less clear examples of 1/*f* scaling in the response variability of dyslexic readers, and an underlying attractor that is less recurrent and deterministic, and yields lower entropy and meanline, compared with the response variability of average readers.

In addition, performance measures relying on 1/*f* noise and RQA were expected to indicate the severity of a reading impairment. We exploited the inter-individual variability by correlating each of the reading performance measures to evaluate this postulate. These measures included mean response time and standardized reading scores at the one hand, and 1/*f* scaling and RQA statistics at the other. This approach allowed for an additional evaluation of the predicted relation between reading fluency and the introduced dynamical performance metrics.

2. Method

2.1 Participants

We performed a word-naming study to test the reading performance of 15 dyslexic children, age 7 to 8. Dyslexic children were recruited in a remediation institute for dyslexia. As a control group, 15 non-dyslexic readers ranging in age from 6 to 7 years old with no history of dyslexia were recruited in a regular elementary school, and performed the same task. All participants were native Dutch speakers.

2.2 Materials

In addition to the word-naming experiment, a test known as the Een-Minuut-Test [One-Minute Test] by Brus and Voeten (1973) was used to assess reading decoding or reading fluency. Oral reading fluency is regarded as the sole best indicator of reading problems or dyslexia (Fuchs, Fuchs, Hosp, & Jenkins, 2001). The word-naming experiment itself consisted of 550 Dutch one-syllable words (2 to 8 letters), with a frequency larger than 0 per million, retrieved from CELEX. Each participant was presented with one out of three randomized lists of the 550 word stimuli on a computer screen, and a voice key recorded the response time with millisecond precision.

2.3. Procedure

All participants were orally instructed to respond as fast and as accurately as possible to the visually presented words. Then, the children were presented with 20 practice trials to make sure they understood the instruction and to calibrate the voice key. Each trial began with the presentation of a fixation point ("+++"), followed by a word. The word disappeared from the screen when an utterance was detected. The inter-stimulus-interval (ISI) was 500 *ms* for both groups of participants. After 550 stimuli were presented, the end of the experiment was announced on the screen. The reaction time series of both groups were taken to compute each participant's average reaction time and standard deviation, as well as 1/*f* noise and RQA measures. To the latter goal, we preceded as follows.

Before being subjected to further analyses, erroneous reaction times were removed. Erroneous reaction times either indicated that the voice key recorded a sound before the stimulus word was read, or that the voice key did not detect the pronunciation. With these largest deviations removed, reaction times larger and smaller than 2* the remaining SD from the mean, were deleted. This was necessary to eliminate inherent biases in the applied time series analyses (see Holden, 2005). Then, the time series were normalized and linearly detrended. Zeros were appended to the normalized time series if a length of 512 data points required for the fractal analyses was not reached (cf. Van Orden et al., 2003). For time series longer than 512 data points, the first data points in those series were removed until 512 trials remained.

2.3.1. Spectral analysis. Spectral analysis transforms data series from the time domain (e.g., milliseconds) into a frequency domain (Hz), through a Fast-Fourier-Transformation. The procedure finds the best-fitting sum of harmonic sine and cosine waves in a data signal, and renders their power (amplitude^2) at each fitted frequency on log-log scales. The total number of estimated frequencies in the Fast-Fourier Transform was 256. The statistic of interest is the slope of the spectral portrait, which captures the relation between amplitudes and frequencies of variation in the data signal. Here, we fitted the spectral slope over the 25% of lowest frequencies (cf. Eke, Hermán, Kocsis, & Kozak, 2002). As shown in Figure 1, a zero slope indicates a random signal, and a slope of -1 indicates 1/*f* scaling.

2.3.2. Standardized Dispersion Analysis. Standardized Dispersion Analysis (SDA) investigates the scaling of variability with changes in sample size. That is, variability is measured using the standard deviation (using the population formula, i.e., using *N*, the number of data points, in the calculation, rather than the usual bias corrected *N – 1*) of means of progressively larger adjacent samples in a time series. That is, the analysis tracks how dispersion in sample means decreases as progressively larger samples of adjacent data points

(bins) are aggregated together in a sample mean. As a first step, the standard deviation is computed for the original data series, which contains 512 data points. The second step involves calculating the standard deviation of the 256 means (bins) of each two consecutive measurements (bin size), and so on. We iterated this procedure until only 16 bins were remaining, each of which represents the mean of 16 adjacent samples in the original time series.

The results from SDA can be seen in a plot of the logarithm of the bin size against the logarithm of the standard deviation, as in Figure 3. For random, white noise, it should not matter that adjacent samples are being grouped and regrouped to form samples of different sizes; for white noise, the slope in Figure 3 is close to -0.5 (see Van Orden et al., 2003, for a detailed description). The outcome of standardized dispersion analysis is expressed by the fractal dimension of a time series, which is given as 1 – the slope of the regression line. Hence, the FD of white noise is 1.5. A shallower slope (i.e., the 1/*f* scaling pattern shown in Figure 3 has a slope of around -0.2) indicates correlated activity across timescales, as expressed by the change in a variance statistic due to changes in bin sample sizes. A fractal dimension thus expresses whether the variance statistic converges fast enough, as sample size increases, to yield a stable population parameter. If not, then the process that produced the variance is scale free and has no characteristic scale or quantity of variance. An in-depth tutorial of both spectral analysis and standardized dispersion analysis can be found in Holden (2005).

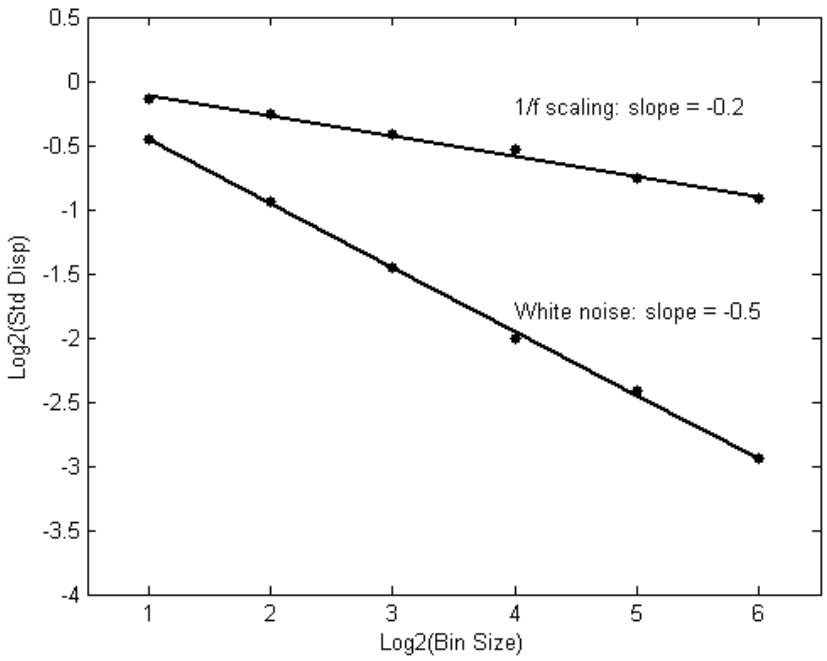

Figure 3. Standardized dispersion is shown as a function of sample-bin size, on log-scales (base 2 was used here). The solid line is the least-squares regression for the six different estimates. Fractal dimension is computed as 1- the slope. The fractal dimension of white noise equals 1.5, whereas a fractal dimension of 1.2 indicates exact 1/*f* scaling.

2.3.3. Detrended Fluctuation Analysis. Detrended Fluctuation Analysis (DFA; Peng et al., 1993) is yet another method to reveal the extent of 1/*f* scaling in behavioral time series, and is especially useful when confronted with nonstationary signals. The first step is to integrate the time series to be analyzed. Next, the integrated time series is divided into bins of equal length,

containing *n* data points. In each bin of length *n*, a least squares line is fit to the data (representing the *trend* in that bin). And then the time series is detrended by substracting the local trend in each bin. From the now integrated and detrended time series, the root-mean-square fluctuation (average fluctuation) is calculated. This computation is repeated over various timescales (bin sizes) to characterize the average fluctuation at each timescale. In the present study, DFA was performed on bin sizes ranging between 2^2 and 2^8 data points (ranging from a few seconds to minutes of performance). The results from DFA are usually shown in a plot of bin size against fluctuation, as in Figure 4, in which the scaling exponent is given by the slope. For 1/*f* scaling, fluctuation will increase with bin size, as indicated by a linear relationship on log scales (yielding a slope of 1). White noise yields a slope of 0.5.

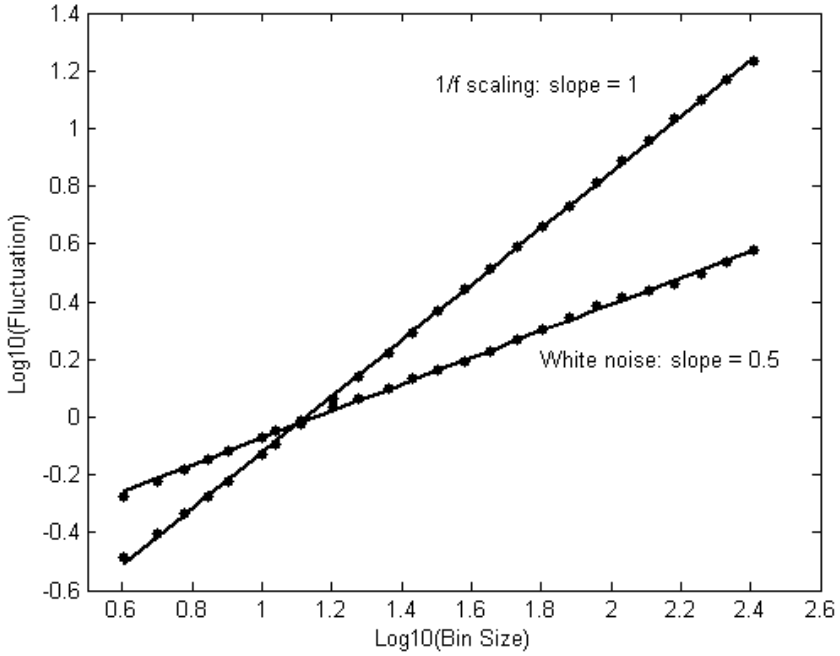

Figure 4. Average fluctuation is depicted as a function of sample-bin size, on log-scales. The solid line is the least-squares regression across timescales. The slope of the regression line equals 0.5 for white noise, and 1 for 1/*f* scaling.

2.3.4. A common scale of Fractal Dimension. The reported fractal dimension statistics were taken from an average of the fractal dimensions across the three estimates (spectral analysis, SDA, and DFA). The outcomes of spectral analyses and DFA were first transformed into a common scale of fractal dimension. For spectral analysis, $FD = (\alpha^2 + 4\alpha + 15) / 10$, where *FD* is the fractal dimension, and α the slope of the power spectrum. For DFA, $FD = 0.4\beta^2 - 1.2\beta + 2$, where β is the slope of the log-plot of bin size against fluctuation. A fractal dimension of 1.5 equals white noise, exact 1/*f* scaling yields a fractal dimension of 1.2.

2.3.5. Recurrence Quantification Analysis (RQA) combines recurrence plots (Eckmann, Kamphorst, & Ruelle, 1987), that is, the visualization of trajectories in phase space, with the objective quantification of nonlinear system properties. That is, time series are delayed with a certain lag or delay and embedded in a phase space with an appropriate dimensionality (Takens, 1981),

$$X_n = [X_n, X_{n+d}, X_{n+2d}, \ldots, X_{n+(m-1)d}],$$

for each data point X_n in a time series, where *m* is the embedding dimension, and *d* is the delay. The *m* number of variables become coordinates in a geometrical space: the phase space of the system. Next, around each point X_n in phase space, an *m*-dimensional sphere, or radius, is calculated. Every time the time series returns within this radius, after having left it, the points that fall within this radius are called recurrent points.

Consequently, measures like recurrence rate change in function of the a priori choice of radius, and thus the radius needs to be chosen carefully. Setting the radius too large diminishes the sensitivity of the analysis, because many (or in the extreme case all) points would be considered recurrent. Likewise, setting the radius too small would cause very few points to be considered recurrent. In the present study, radius was set to 20% of the maximum Chebychev distance in phase space, which corresponded roughly to a recurrence rate between 0.05 and 0.10 (cf., Riley et al., 1999) to reassure that the range of individual outcomes was not restricted in either direction for both experimental groups.

Other parameters that affect the outcome of RQA measures, and thus need to be chosen carefully, are the time lag or delay, and the embedding dimension. Here a delay of 1 data point was combined with an embedding dimension of 6. The choice for delay was based on the Average Mutual Information function (AMI), which is a form of autocorrelation function that provides information about the predictability of $X(t + x)$ given a measurement $X(t)$ over a range of possible choices of delay (Fraser & Swinney, 1986). Because it is desirable in a phase space reconstruction for each surrogate dimension to reveal something new about the dynamics (i.e., to reveal the smallest mutual information), the first local minimum of the AMI function was chosen as the optimal delay.

The choice for embedding dimension was based on global False Nearest Neighbor analysis (Kennel, Brown, & Abarbanel, 1992), which reveals how much information would be gained by adding additional surrogate dimensions. That is, when phase space is projected in too small a number of embedding dimensions, non-neighboring points could be misconceived as (false) neighbors. Choosing embedding dimension too high would be not useful either, because there is nothing more to gain by adding another dimension, since the percentage of false nearest neighbors no longer drops while the algorithmic complexity of the analysis increases. A final parameter is the minimal line length for identifying deterministic segments; here, each sequence of minimally 2 recurrent points was considered a recurrent pattern. An additional check to reassure that the outcomes were robust over a range of input parameters was to use different input parameters, which revealed consistent results (cf. Riley et al., 1999; Riley & Van Orden, 2005).

The next step is to quantify complexity measures in the reconstructed phase space. The first measure is Recurrence Rate, which is computed as the ratio of the number of recurrent points in phase space over the total number of points in phase space. By construction, Recurrence Rate varies between 0 and 1 (sometimes recurrence rate is displayed as a percentage, however). Determinism is defined as the ratio of the number of recurrent points forming a recurrent pattern over the total number of recurrent points in phase space. Entropy is computed as the Shannon entropy of a histogram in which the number of deterministic segment lengths of different lengths is counted and distributed over integer bins of the histogram, where each bin represents a possible length of a recurrent pattern as empirically determined based on the frequency with which determinsitic patterns of different lengths are observed. Entropy is computed as $-\Sigma(P_b)\log_2(P_b)$, where P_b indicates bin probabilities of all nonzero bins greater than or equal to the number of recurrent points defining a recurrent

pattern (cf. Webber & Zbilut, 1994). For example, if 100 upward diagonal lines—ten each of ten different lengths—are observed, then the probability of a given line falling in a given nonzero bin is 0.1. Meanline is the average duration of deterministic patterns in that distribution. Detailed tutorials that include a careful examination of RQA are Marwan et al. (2007), Riley, Balasubramaniam, and Turvey (1999), and Riley and Van Orden (2005). The RQA analysis was run using Marwan's CRP Toolbox for Matlab (available at: http://www.recurrence-plot.tk).

3. Results

3.1. Group Differences

The descriptive statistics of each of the measured variables are presented in Table 1. As expected, the dyslexic readers showed slower response times, larger intra-individual variability in response time (standard deviation), more pronunciation errors, and lower One-Minute-Test scores, compared with the non-dyslexic readers. Also the fractal dimension statistic distinguished between dyslexic and non-dyslexic reading performance. As predicted, the temporal structure of response times was closer to white noise in dyslexic response times and clearer examples of 1/*f* noise emerged in non-dyslexic response times. The magnitude and dispersion of this difference can be seen in Figure 5.

Table 1.
Descriptive Statistics of the Measured Variables

	Non-dyslexic readers (N = 15)	Dyslexic readers (N = 15)	
	Mean (SD)	*Mean (SD)*	*t (28)*
One-Minute-Test	51.80 (9.64)	31.53 (12.35)	5.01**
Response Time	704 (152) *ms*	1793 (888) *ms*	-4.68**
Standard Deviation	400 (148) *ms*	1281 (624) *ms*	-5.32**
Accuracy	92 (7.6) %	79.2 (10.8) %	3.76**
Fractal Dimension	1.38 (0.08)	1.45 (0.07)	-2.62*
Recurrence Rate	0.09 (0.05)	0.04 (0.05)	2.21*
Determinism	0.88 (0.04)	0.79 (0.10)	3.16**
Entropy line length	1.88 (0.23)	1.58 (0.35)	2.70*
Meanline	4.01 (0.63)	3.45 (0.68)	2.33*

** $p < .01$, * $p < .05$, two-tailed.

Also, each of the RQA measures differentiated among dyslexic and non-dyslexic readers. Dyslexic response times yield lower recurrence rates compared with non-dyslexic response times (see Figure 6a). Also, the attractor underlying dyslexic reading performance is less deterministic or patterned, as shown in Figure 6b, and less complex (Figure 6c). The final RQA measure, meanline, reveals that the dynamics of dyslexic reading performance are less stable than non-dyslexic reading performance (shown in Figure 6d).

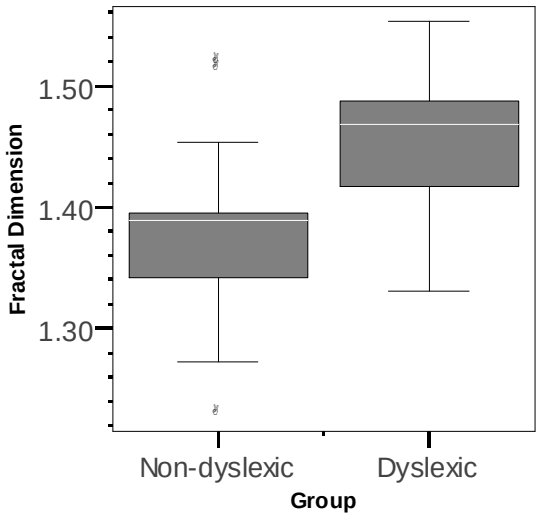

Figure 5. The difference in Fractal Dimension (y-axis) between response series of dyslexic and non-dyslexic readers (x-axis).

We may conclude that the temporal dynamics of response variability are sensitive to variations in reading fluency. The word-naming performance of non-dyslexic readers combined fast and stable responses to word stimuli with clearer examples of 1/*f* noise. Non-dyslexic reading performance also showed a more confined attractor (higher recurrence rate) that is more regular and patterned (higher determinism), more complex (higher entropy), and more stable (longer meanline).

3.2. Within-Group Correlations among Measured Variables

With the differences in each of the measured variables between dyslexic and non-dyslexic word-naming performance spelled out, the next step was to investigate the correlations among these variables within each experimental group. Table 2 shows the correlation profile for the dyslexic and the non-dyslexic group separately.

In the dyslexic group, mean response time and One-Minute Test (EMT) reading scores correlate strongly with the fractal dimension statistic and the RQA outcomes. Specifically, more severe cases of dyslexia, indicated by slower response times and lower score on the reading test, produce higher fractal dimensions (less clear examples of 1/*f* noise; range = 1.33 – 1.55) compared with less severe cases of dyslexia. In addition, a more severe reading impairment is accompanied by a lower recurrence rate, lower determinism, lower entropy, and a shorter meanline. Thus, less severe cases of dyslexia show a higher recurrence rate, and more determinism, entropy and meanline than more severe cases of dyslexia. In the control group, these strong correlations were absent; fractal dimension and RQA outcomes were independent from mean response time and One-Minute-Test (EMT) reading scores. The only exceptions are the correlations of fractal dimension and determinism with standardized reading scores, which replicated the relation observed in the dyslexic group in a slightly weakened form.

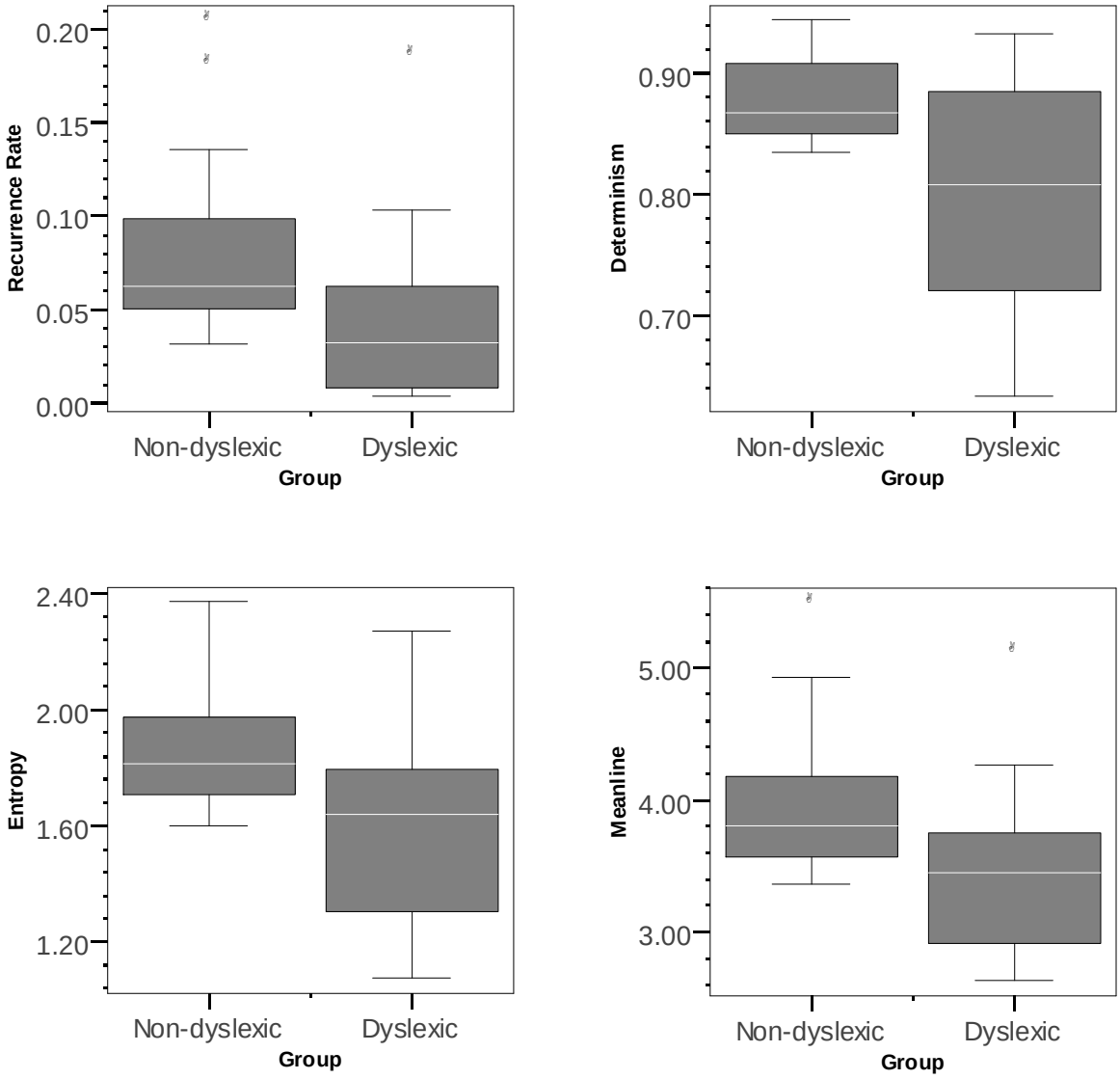

Figure 6a-d. Differences in RQA measures recurrence rate (a), determinism (b), entropy (c), and meanline (d) between dyslexic and non-dyslexic readers.

4. Discussion

The present study reveals that young dyslexic readers not just read slower and more variably than non-dyslexic readers. Dyslexic readers equally reveal more random trial-to-trial variability, and thus showed less clear examples of 1/*f* scaling in their response times compared with average readers. The results from Recurrence Quantification Analysis (RQA) provided more detailed information about these distinct dynamical patterns of response time. The system dynamics underlying dyslexic reading performance are less confined, patterned, complex, and stable than dynamics underlying non-dyslexic reading performance.

Also the pattern of correlations between aggregate measures of reading fluency (mean response time and standardized reading score) at the one hand, and the dynamical metrics

Table 2.
Two-Tailed Pearson Correlation Coefficients of Mean Response Time (RT) and the One-Minute-Test (EMT) with Fractal Dimension and RQA Outcomes for both Groups of Readers.

		Fractal Dimension	Recurrence Rate	Determinism	Entropy	Meanline
Dyslexic readers	RT	.56*	-.70**	-.88**	-.81**	-.77**
	EMT	-.77**	.84**	.75**	.79**	.83**
Non-dyslexic readers	RT	.21	-.10	-.12	-.25	-.24
	EMT	-.54*	.37	.53*	.43	.41

** p <.01, * p <.05, two-tailed.

based on 1/*f* scaling and RQA at the other, confirm these differences. While the former metrics loosely relate to the latter metrics in non-dyslexic reading performance at most, the opposite is true for dyslexic reading performance. In the group of dyslexic readers, we observed strong correlations among static and dynamical measures of reading fluency, ranging from 0.5 to 0.9. The implication is that a fuller understanding of learning disabilities like developmental dyslexia may actually require going beyond the aggregate level of analysis of central tendency measures (cf. Gilden & Hancock, 2007).

Together, these findings raise the broader question of the linkage between cognitive dynamics and reading fluency. Why is it that dyslexic naming latencies vary more randomly from trial-to-trial than average naming latencies, and even more so when the reading impairment is more severe? We argue that in cognitive performances, as in physical and physiological systems, the presence of 1/*f* scaling indicates the coupled activity of processes that evolve over multiple timescales. That is, the presence of 1/*f* scaling suggests that the involved components interact so completely that one can no longer parse their individual contributions in the collective activity of the whole system. While each component may contribute its own potentials and constraints, the activity of each component is strongly interdependent with the activities of potentially many other components. This postulate entails that clearer 1/*f* scaling expresses a closer cooperation among task-specific processes nested across different timescales, and could explain why the extent of 1/*f* scaling so strongly relates to functional levels of reading performance (i.e., reaction times and standardized reading scores).

In this study, 1/*f* scaling analyses were assisted by RQA in an effort to understand how well-coordinated behavior (i.e., fluent reading) emerges in the balance of independent versus interdependent component activities. RQA was used to further investigate the emergence of spontaneous temporal order in naming latencies, using the mathematical concepts of self-organization. These concepts inform about how empirically observed temporal patterns can be mapped on simple low-dimensional control principles. That is, in the physical sense, any system described by low-dimensional dynamics is composed of, and coupled to, many subsystems, thereby causing them to fluctuate in an unexpectedly orderly manner over time (i.e., independent trajectories of the system approach each other in phase space). These patterns arise solely as a result of the dynamics of the system with no specific ordering influence from the outside or homunculus from the inside. Therefore, these patterns are referred to as self-organized patterns; the pattern formation is entirely due to the dynamic interaction among the many components that compose the system.

The present results suggests that the cognitive organization under scrutiny is not so much a serial chain of processing components, each adding independently to the duration of each response, but more one of characterizing loops and levels of interdependence in entangled cognitive phenomena (Bell, 1999). But admittedly, one may wonder why one would want to take such a 'complex' position to observe reading fluency while 'simple' mean values, when contrasted (i.e., in an ANOVA), reveal so much specific information about the system as well. What insights, specifically, are there to gain from this relatively unexplored area of human performance?

Most obviously, we demonstrated that the here introduced methods extend the methodological toolbox available to reading research. The introduced concepts (fractal scaling, recurrence, determinism, entropy, etc.) are mathematically well-defined and open to observation with 1/*f* scaling analyses and RQA. More specifically, these methods allow constructing testable predictions for interaction-dominant approaches to human cognition. In the present study, for instance, it was expected a priori that the dynamical properties of word-naming latencies would be so closely related with reading fluency. That is, the more extensive the interdependence among components, the more coordinated and efficient the resultant behavior. Conversely, reduced system interactions, as in developmental dyslexia, yield impaired performance. Although admittedly exploratory, the present study allows starting to get better grips on the full-blown complexity inherent to fluent reading.

The present results allow speculating more broadly about the nature of developmental dyslexia than before. For instance, in the introduction we raised the question why is it that such a diverse set of empirical findings successfully differentiate between dyslexic and non-dyslexic reading performance. This empirical fact in itself allows that multiple contrasting accounts of developmental dyslexia may be supported simultaneously. The observation that dyslexic children fall out on so many different tasks and modalities is not so strange from the position of interaction-dominant dynamics, however. Interaction-dominant dynamics do not assume specific component deficiencies to underlie developmental dyslexia, but rather a much more general reduction of system interactions (and hence, coordination) among multiple task-specific processes. It may in fact only be logical that developmental dyslexia shows itself in so many different facets of performance, simply because the linguistic, perceptual, motor, and physiological processes involved in fluent reading so massively interact.

In sum, the present study reveals that trial-by-trial variability provides psychologists with much more information about the system under scrutiny than would be expected under the assumption of random noise. The finding that the dynamical structure of response time series distinguishes between dyslexic and non-dyslexic readers is new, but aligns with similar findings from other tasks and domains (Diniz et al., 2010; Gilden & Hancock, 2007; Hausdorff, 2007; Goldberger et al., 2002; Kello et al., 2007; Van Orden et al., 2009; Wijnants et al., 2009). In addition, the relative presence of 1/*f* noise and the description of coordination dynamics offered by RQA effectively reveal the severity of the reading impairment. To our knowledge no contemporary models and theories of dyslexia exist that anticipate such an effect, although Greijn (2011) and Van Orden, Holden, Wijnants, & Bosman (2010; based on Holden et al., 2009), might be important steps along the way.

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Chapter 5

Does sample rate introduce an artifact in spectral analysis of continuous processes?

Based on:

Wijnants, M. L., Cox, R. F. A., Hasselman, F., Bosman, A. M. T., & Van Orden, G. (invited resubmission). Does sample rate introduce an artifact in spectral analysis of continuous processes? *Psychological Methods.*

CHAPTER 5

Abstract

Spectral analysis is a widely used method to estimate $1/f^{\alpha}$ noise in behavioral and physiological data series. The aim of this paper is to achieve a more solid appreciation for the effects of periodic sampling on the outcomes of spectral analysis. It is shown that spectral analysis is biased by the choice of sample rate because denser sampling comes with lower amplitude fluctuations at the highest frequencies. Here we introduce an analytical strategy that compensates for this effect by focusing on a fixed number, rather than a fixed percentage of the lowest frequencies in a power spectrum. Using this strategy, estimates of the degree of $1/f^{\alpha}$ noise become robust against sample rate conversion and more sensitive overall. Altogether, the present contribution may shed new light on known discrepancies in the psychological literature on $1/f^{\alpha}$ noise, and may provide a means to achieve a more solid framework for $1/f^{\alpha}$ noise in continuous processes.

1. Introduction

Over recent decades, there has been an increasing interest in the time-evolutionary properties of psychological data series, and the number of methods to quantify the *degree-of-randomness* in time series data is rapidly expanding. It is becoming increasingly acknowledged that the variation from one measurement to the next rarely fluctuates randomly, as traditionally assumed in most standard statistical methods (Gilden, Thornton & Mallon, 1995; Gilden, 2001; Van Orden, Holden, & Turvey, 2003). Especially the presence of $1/f$ noise (also called $1/f$ scaling or pink noise) in repeated performances is a robust finding. The presence of $1/f$ noise implies that a data signal may not be accurately described without incorporating time at the level of analysis. We will first explain the workings of spectral analysis through a fictive example, and then we explain how spectral analysis can be used to estimate the presence of $1/f$ noise.

Consider a participant, performing a 500-trial simple response task. The task instruction is, for instance, to press a button whenever a stimulus is presented. The dependent variable of interest for the researcher is response time to the stimulus. This participant's average response time turns out be 500 ms with a standard deviation of 35 ms. However, this participant's task performance constitutes the unrealistic case where the pattern of response variability over time looks exactly like a sine wave (see Figure 1a). Now, imagine another participant, who received the same task instruction, and showed exactly the same response times but in a different trial order (see Figure 1c). While both response series have an identical mean and standard deviation, they show a distinct pattern of responses over time.

Statistics based on central tendency measures are not sensitive to the different pattern of variability observed in both participants. If in one experimental group all participants were like participant 1, and in another experimental group all participants were like participant 2, a *t*-test for instance, would not differentiate among both groups because the groups would yield equal means and standard deviations. Yet, a different inherent process likely produced the responses. Thus, a researcher may wonder whether trial-to-trial fluctuations observed in an experiment occur randomly or not, and ask whether there is anything systematic about the observed temporal patterns of variation.

Spectral analysis is one of the available methods to estimate the degree of randomness in a pattern of responses over trials. Spectral analysis translates dependencies in the time domain

(i.e., a pattern of change in response time over trials) as simple features in the frequency domain using an operation called a Fourier transform, which decomposes the data series containing changes in response over trials into its constituent frequencies. Next, the power (the square of the amplitude) at each frequency in the decomposed signal is plotted in a so-called a power spectrum (also called power spectral density function). For instance, a power spectrum of participant 1's response series (shown in Figure 1b) reveals one peak at the dominant frequency of the sine wave. Participant 2's responses do not yield a dominant frequency in the time domain, and consequently a spectral analysis does not reveal any peaks in the power spectrum (see Figure 1d). Thus, while the performances of both participants are indistinguishable using central tendency measures, the two different temporal arrangements of the same responses are distinct in the frequency domain. The power spectrum thus provides information which effectively complements information from *t*-tests, ANOVA's, etc. (see Slifkin & Newell, 1998; Riley & Turvey, 2002, for more examples).

Spectral analysis can not only be used to detect simple periodicities as in the example above, but can also be used to quantify more complex and realistic patterns of variation in psychological data series. Consider, for instance, another participant in the simple reaction task whose response times show a pattern of variability called 1/*f* noise, as shown in Figure 2a. 1/*f* noise is a complex sequence effect spanning over the entire time course of an experiment, and comprises undulating "waves" of relatively longer and then shorter response times that

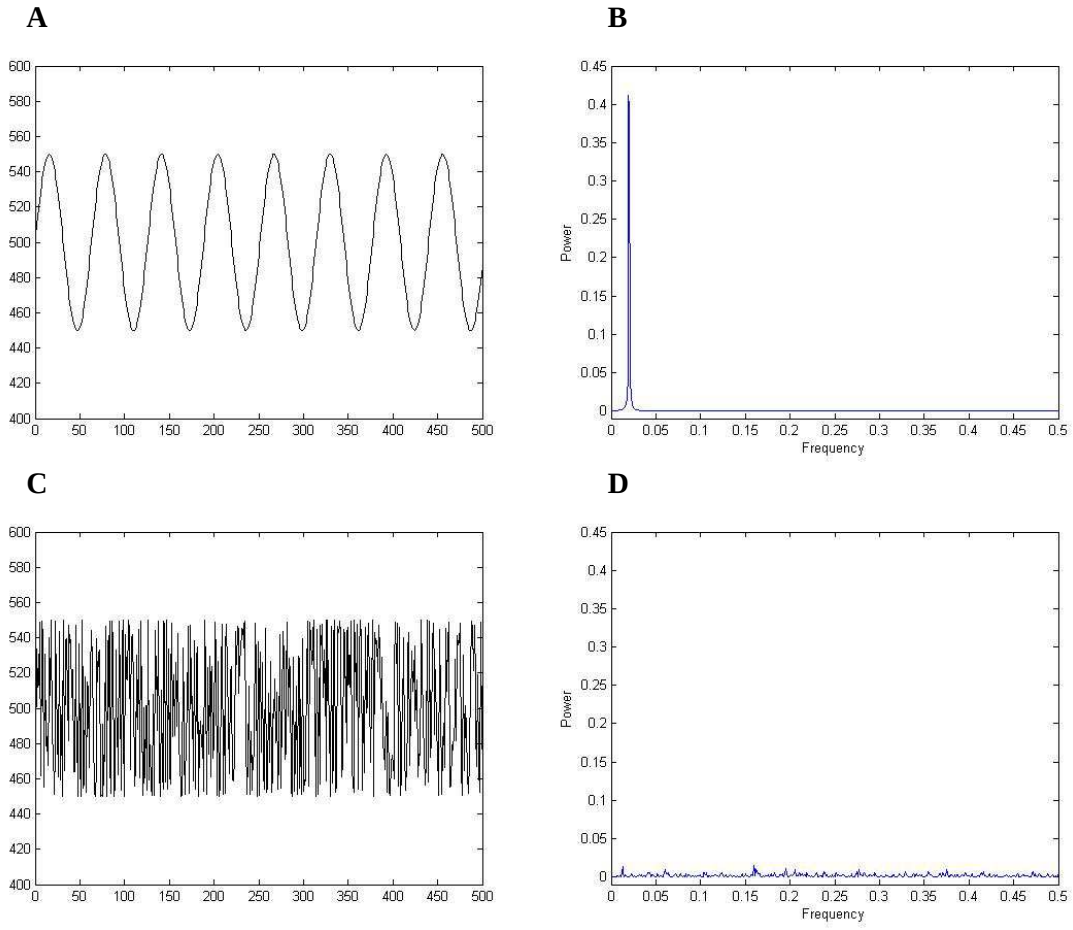

Figure 1. Figure 1a shows a fictive data series yielding response times oscillating as a sine wave (in milliseconds, y-axis) over trials (x-axis). Figure 1b shows a power spectrum of the fictive data series shown in Figure 1a; note the peak. Figure 1c shows the same data series as Figure 1a after

randomization. Figure 1d shows a power spectrum of the randomized data series shown in Figure 1c; note the absence of a peak.

travel across the series. In a 1/*f* signal, faster (high-frequent) changes in response time are typically small, and embedded in overarching, slower (lower-frequent) changes of higher amplitude. In only a few simple steps, this characteristic pattern of response variability can be observed through spectral analysis. First, a Fourier transform translates the data series into the sum of sines and cosines that best fits the data series. This is schematically represented in Figure 2b. Next, the frequency and power (amplitude^2) of each of the fitted waveforms are plotted against each other in a power spectrum (see Figure 2c). Figure 2d shows the power spectrum on log-scales, which makes the 1/*f* noise pattern even more visible; power is in inverse proportion to frequency. The log-log power spectrum in Figure 2d yields a slope of -1 (hence, $1/f^1$ noise).

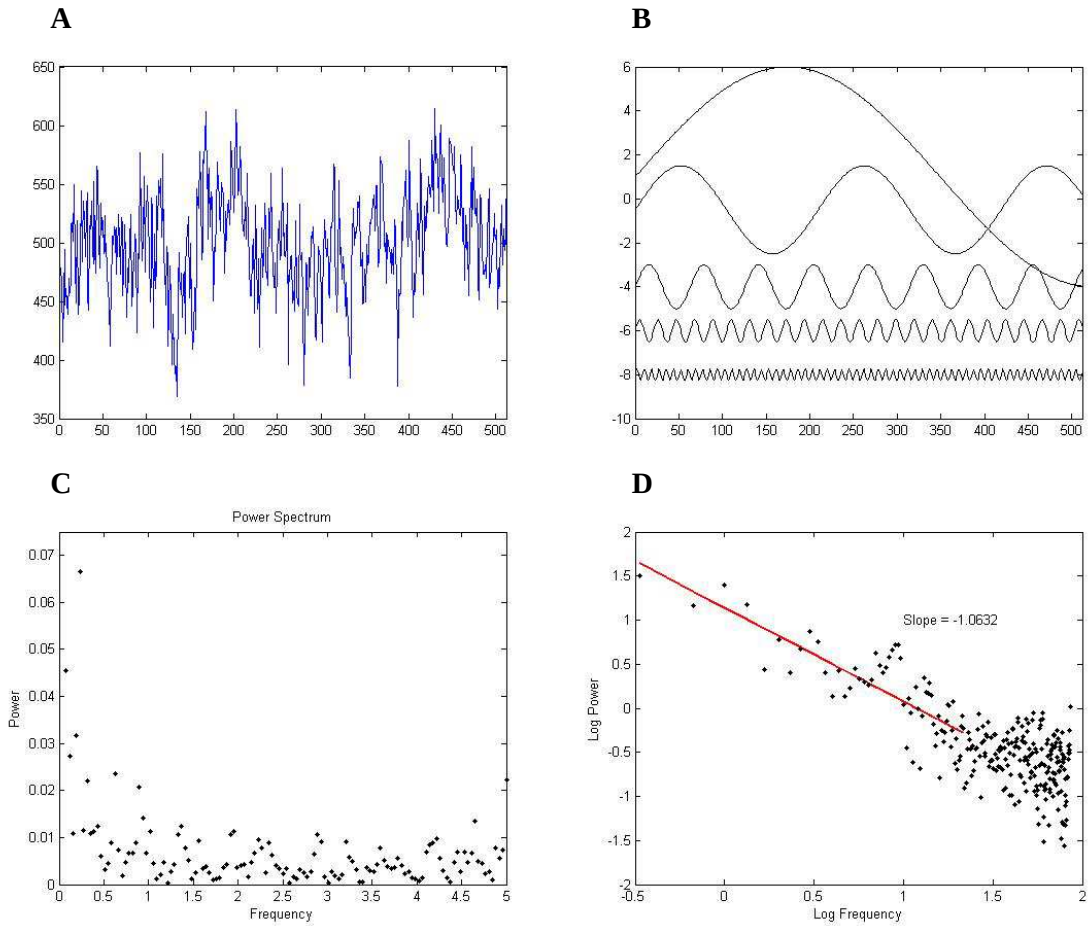

Figure 2. Figure 2a shows a response series yielding 1/*f* noise. Figure 2b schematically represents a number of sine waves which are fitted to the data series through a Fourier transform. Figure 2c shows the 1/*f* noise pattern in a power spectrum, which is shown on logarithmic scales in Figure 2d. The slope in Figure 2d was fitted over the 25% of lowest frequencies.

Observing 1/*f* noise may run against standard statistical intuitions because the variability in psychological data is usually assumed to fluctuate randomly from trial to trial. A data series with random background noise (also called white noise, see Figure 3a), however, does not yield a relationship among frequency (*f*) and a particular change of amplitude S(*f*) in the signal (see Figure 3b). A power spectrum of white noise variability has a flat slope on log scales ($\alpha = 0$, yielding $1/f^0$ noise). A third category of noise is called Brownian noise (see

Figure 3c), and can be described as $1/f^2$ noise (see Figure 3d; the slope is -2). Brownian noise is also called a random walk, because it can be produced by adding a random increment to each sample to obtain the next. In contrast to white noise, which can be produced by randomly choosing each sample independently, Brownian noise yields persistence or memory in the data series.

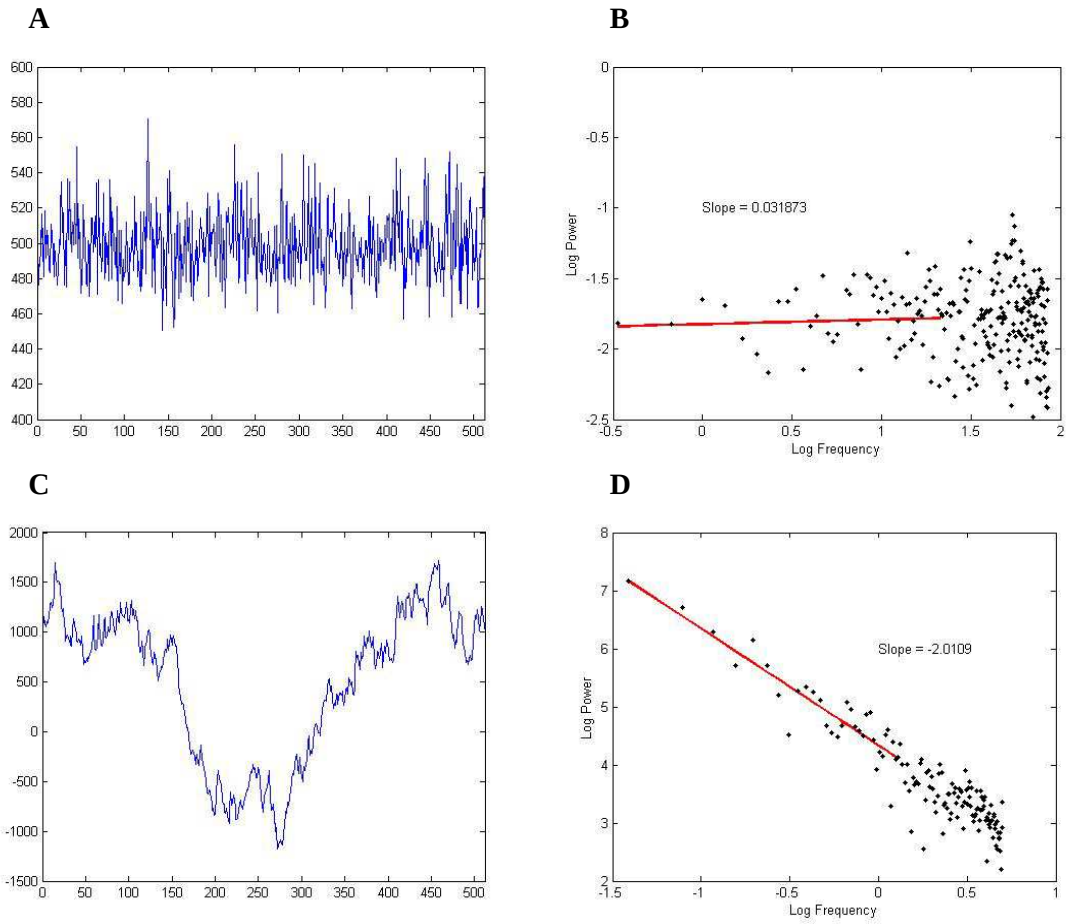

Figure 3. Figure 3a shows an example of white (random) noise. The power spectrum of the white noise series is shown in Figure 3b. Figure 3c shows an example of Brownian noise. The power spectrum of the Brownian noise series is shown in Figure 3d. The slopes in Figure 3b and 3d were fitted over the 25% of lowest frequencies.

1.1. 1/f noise in human performance

1/*f* noise has been observed in repeated responses in many cognitive tasks. Examples include simple and choice reaction (Kello, Beltz, Holden, & Van Orden, 2007), mental rotation (Gilden, 1997), visual search (Aks, Zelinsky, & Sprott, 2002), lexical decision (Gilden, 1997), word naming (Van Orden et al., 2003), color and shape discrimination (Gilden, 2001), implicit associations (Corell, 2008), and self-reports of self-esteem (Delignières, Fortes, & Ninot, 2004), to name a few examples. Apart from the ubiquitous presence of 1/*f*-like noise in cognitive performances (Kello et al., 2007), 1/*f* noise has been observed in temporal patterns of variation at all levels of neural (Werner, 2010) and physiological organization (West, 2010).

The origins of 1/*f* noise in human cognition remain a theoretical topic of debate, however (Diniz et al., 2010; Torre & Wagemakers, 2009; Van Orden et al., 2003; 2005; Wagenmakers, Farrell, & Ratcliff, 2005). Nonetheless, the relative presence of 1/*f* noise (hence, the slope - α)

has empirically been shown to distinguish among experimental conditions (Diniz et al., 2010; Kello et al., 2007; Van Orden, Kloos, & Wallot, 2011, are reviews). Therefore, the slope of a power spectrum is an informative measure in psychological research. The scaling exponent α in $1/f^{\alpha}$ noise usually varies between white noise and $1/f$ noise ($0<\alpha<1$), but sometimes also between $1/f$ noise and Brownian noise ($1<\alpha<2$).

Intriguingly, empirical evidence has accumulated suggesting that the relative presence of $1/f$ noise is related to the coordination of cognitive and physiological processes. For instance, deviations from $1/f$ noise (either towards white noise or towards Brownian noise) have been found with epilepsy (Ramon, Holmes, Freeman, McElroy, & Rezvanian, 2008), heart failure (Goldberger et al., 2002), fetal distress syndrome (Goldberger, 1996), major-depressive disorder (Linkenkaer-Hansen et al., 2005), mania (Bahrami, Seyedsadjadi, Babadi, & Noroozian, 2005), attention-deficit-hyperactivity-disorder (Gilden & Hancock, 2007), developmental dyslexia (Wijnants, Hasselman, Cox, Bosman, & Van Orden, 2011), autism (Lai et al., 2010), Alzheimer's disease (Abásolo, Hornero, Gómez, García, & López, 2006), Huntington's disease (West, 2006), and Parkinson's disease (Hausdorff, 2007). In addition, the presence of $1/f$ noise correlates, for instance, with the severity of depression symptoms (Linkenkaer-Hansen et al., 2005), the success rate of recovery from traumatic brain injury (Burr, Kirkness, & Mitchell, 2008), and falling risk in elderly (Hausdorff, 2007). Also, the presence of $1/f$ noise increases with learning (Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009) and may decrease as task demands increase (Clayton & Frey, 1997; Correll, 2008). In each case the overly random or overly rigid behaviors showed a value of α further from 1, compared to conditions allowing for more flexibly stable and adaptive performances.

These studies confirm the importance of time series methods like spectral analysis in psychological research. Interestingly, however, all of the examples above are based on the analysis of *trial series* or interval series. In a trial series, each sampled data value represents a measure of a discrete response or response interval, as in the example of the simple reaction task mentioned earlier. Many variables in psychological research, however, are continuous in nature, rather than discrete. Continuous processes are represented as a *time series* through periodic sampling. Periodic sampling means that the continuous process $x \rightarrow (t)$ is digitized as a sequence of discrete data values $t_1, t_2, t_3, t_n \ldots$, where the total number of data points depends on the chosen sampling rate. Interestingly, however, the clear framework suggested by the role of $1/f^{\alpha}$ noise in trial series has not (yet) found a univocal parallel in the analysis of psychological time series.

Here, we investigate whether differences in sample rate constitute an artifact which obscures comparisons across studies and experimental conditions. The paper is organized as follows. First, a number of details pertaining to analytical choices for spectral analysis are discussed. Then, it is discussed in which way sample rate affects the frequency content of a time series, and it is explained how this artifact is usually dealt with in psychological studies of $1/f^{\alpha}$ noise relying on continuous processes. Next, we show how this approach renders heterogeneous estimates of the slope -α, and offer an alternative solution which circumvents the artifact.

1.2. 1/f noise and periodic sampling

Psychologists are in general well aware of the characteristics of a desired sampling regime. That is, any signal that has been periodically sampled can only be perfectly reconstructed if the sampling rate corresponds to a frequency that is minimally twice the highest frequency in the original signal (this is known as the Shannon-Nyquist sampling theorem; Shannon, 1949). When sampling more sparsely, a phenomenon called aliasing is likely to occur. Aliasing means that fluctuations outside of the measured frequency range are misinterpreted as

different frequencies that fall within the measured range of frequencies, yielding distorted results (see Holden, 2005). Therefore, sample rate is an important input parameter when applying spectral analysis to periodically sampled data series. The estimated frequencies should not be faster than half the sample rate. For example, when a given time series is sampled at 100 Hz, the frequencies estimated in spectral analysis (the x-axis in the power spectrum) should fall in the range of 0 to 50 Hz to avoid aliasing.

The next input parameter for spectral analysis is the number of frequencies to be estimated within the non-aliased frequency range. This parameter will determine the number of data points in the power spectrum. A spectral analysis with maximum frequency resolution will estimate half as many frequencies as there are data points, because the highest resolvable frequency oscillates back and forth every other data point. In order to understand why the regression fit over the 25% lowest frequencies covers such a substantial portion of the power spectrum (as can be seen in Figures 2d, 3c, and 3d), note that a Fourier transform evaluates the power of each frequency within the signal equidistantly within the desired frequency range. After the log transformation, however, the frequencies are no longer equidistant, and exponentially more frequencies are observed in the high-frequency range than in the low-frequency range of the power spectrum.

When the goal of the spectral analysis is to estimate the α scaling exponent (thus, the negative slope of the logarithmic power spectrum, or the presence of 1/*f* noise), another choice concerns the number of frequencies in the power spectrum over which the slope is fitted. That is, the slope -α is rarely fitted over all frequencies, because it is known that a power spectrum often gives unreliable results in the highest frequency range. Specifically, the right-hand side of a power spectrum often presents a flattening (or whitening) of the slope (Holden, 2005; Holden, Choi, Amazeen, & Van Orden, 2010). Therefore, excluding the highest frequencies in the log-log regression is generally recommended (Beran, 1994; Eke et al., 2000; Eke, Hermán, Kocsis, & Kozak, 2002; Holden, 2005). The linear fit is often limited to the 25% lowest frequencies that compose the spectral slope (Eke et al., 2000; 2002) or even 10% (Taqqu, Teverovsky, & Willinger, 1995), to achieve more reliable scaling estimates of the scaling exponent α.

1.3. The 'artifact' of sample rate

The aim of this study is to achieve a more solid appreciation for the effects of periodic sampling on the outcomes of spectral analysis. Specifically, a researcher's choice of sample rate is known to change the estimated α exponents in a particular way (Carlini, Bizzarri, & Cannistraro, 2002; Eke et al., 2002), and this bias is usually not anticipated. This is especially problematic when different studies are compared, which employ a different sampling regime of similar performances (i.e., comparing the outcomes of spectral analysis of trial series with outcomes of spectral analysis of time series), or which rely on periodic sampling but employ different sample rates.

Carlini et al. (2002) point out that higher sample rates yield steeper spectral slopes, hence larger α scaling exponents, compared with more sparsely sampled processes. "The amplitude of the [*highest frequency*] oscillations themselves decreases sharply [*when sample rate increases*] (Carlini et al., 2002, p.246, emphasis added for terminological consistency). Eke et al. (2002) add: "Increasing f_s [*sample rate,*] … cannot continue beyond some upper limit for exceeding it would increase the chance that high-frequency estimates in the power spectrum

would not reflect physiology [*or more generally, the process of interest*].” (Eke et al., 2002, p.27, emphasis added).
These observations constitute the core measurement problem raised in this paper: the outcomes of spectral analysis hinge on sample rate. The logic is simple, and is visually presented in Figure 4a-d, which shows the same one-second time window yielding measurements of an arbitrary process at different sample rates. The time series in Figure 4a was sampled at 200 Hz, and thus contains 200 data points within the one-second window. In Figure 4b, 4c, and 4d show the same segment sampled at 100 Hz, 50 Hz, and 25 Hz respectively. The effect of sample rate on the frequency content of a time series can be seen by eye. The highest frequencies in each of the time windows differ in amplitude; the faster the process is sampled, the lower the amplitude at the highest frequencies in the signal.

The line of reasoning so far is straightforward, but can make a world of difference nonetheless concerning the utility of spectral analysis when confronted with periodically sampled, continuous processes. That is, the highest-frequency range in the spectrum has lower amplitude when higher sample rates are employed, and this artifact gradually protrudes into lower frequencies as sample rate increases. Correctly, some authors have assumed that such an artifact does not affect the estimate of α, given that the biased frequencies are not used to fit the slope -α: “This would not be much of a problem if the upper 75% of the spectral estimates were to be discarded as recommended and if these irrelevant estimates would fall into the discarded range” (Eke et al., 2002, p. 27-28). In other words, the challenge is to focus on the range of frequencies that is not contaminated by the artifact. If, however, the biased frequencies exceed the highest 75% frequency range, the assumption cited above would not be valid, and different values of α would be obtained with different sample rates. Thus, the question is whether the non-contaminated frequency range converges on the 25% lowest-frequency range.

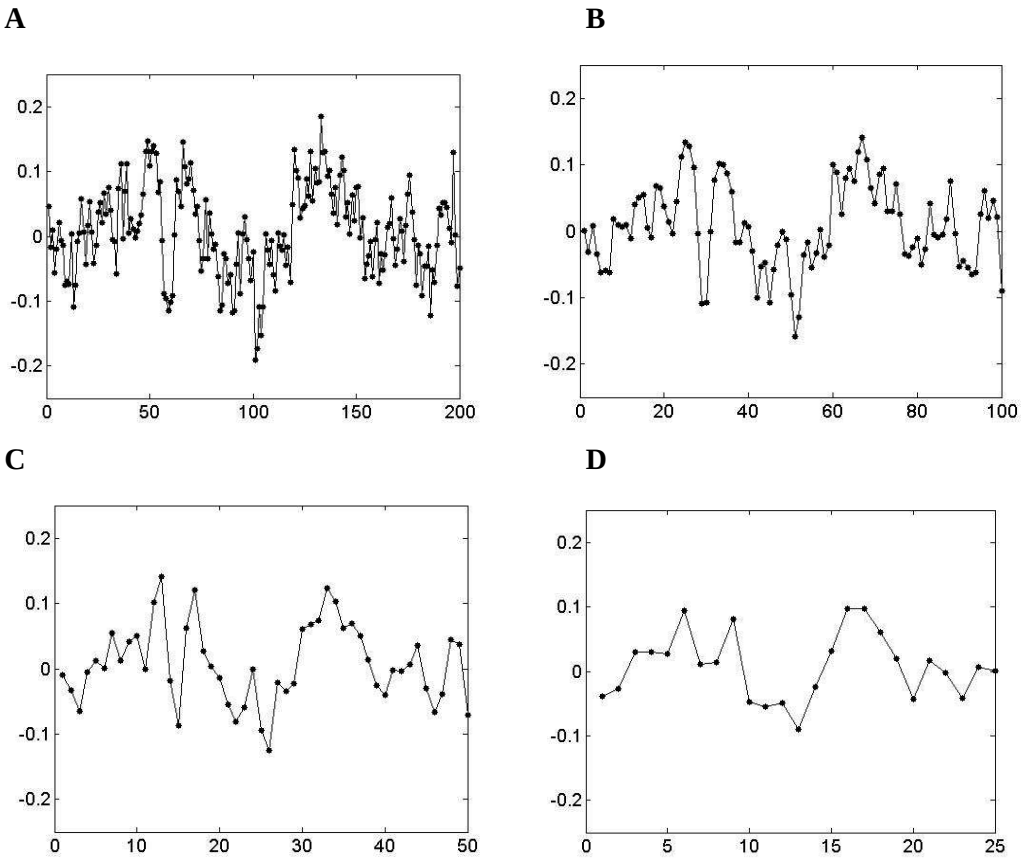

Figure 4. The same arbitrary process measured for one second at either 200 Hz (a), 100 Hz (b), 50 Hz (c), or 25 Hz (d).

To answer the question, we evaluated a Galvanic Skin Response time series that was sampled at either 200 Hz (yielding a time series of 2^{16} data points), 100 Hz (2^{15} data points), 50 Hz (2^{14} data points), or 25 Hz (2^{13} data points). For each sample rate of the same time series, the frequencies in the power spectrum range between 0 Hz and half the sample rate to avoid aliasing. Then, following Eke et al. (2002), the linear regression fit was plotted over the 25% lowest frequency range, to estimate α. (see Figure 5a-d; the discarded 75% frequency range is represented as a horizontal line). Remarkably, Figure 5a-d show rather variable estimates of the spectral slope -α for the same measured process; α ranged between 1.56 and 2.57 depending on sample rate. In other words, even with all precautions in place, sample rate still distorts the estimate of α.

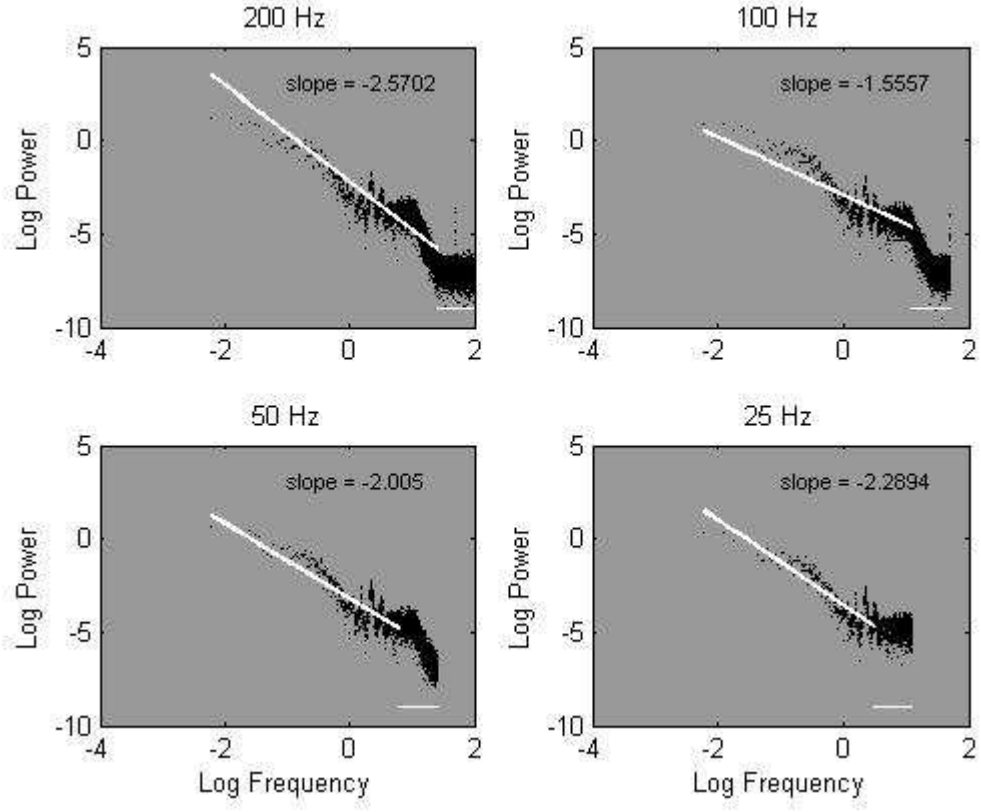

Figure 5. Power spectra estimated from one Galvanic Skin Response time series sampled at 200Hz (a), 100Hz (b), 50Hz (c), and 25Hz (d). Spectral slopes are fitted over the lowest 25% of 2^{15} (a), 2^{14} (b), 2^{13} (c), and 2^{12} (d) estimated frequencies. Note that most of the estimated frequencies fall in the high-frequency range of the spectrum.

Here, we introduce an alternative solution to the problem that outcomes of spectral analysis can hinge on sample rate. The logic is to fit the slope -α over a fixed amount (i.e., 50), rather than over a fixed percentage (i.e., 25%), of lowest frequencies. This solution takes advantage of, rather than being contaminated by, inherent differences in sample rate. Since more frequencies are estimated overall from more densely sampled time series, fitting the slope -α over a fixed number of low-frequencies implies a fit over a lower percentage of low frequencies when a time series is sampled more densely. Thus, while the bias leaks into more of the lower frequencies for higher sample rates (hence, Figure 4a-d), a lower percentage of low-frequencies is used to fit the slope -α. At sparser sample rates, the bias extends over a smaller portion of the low frequencies, and a larger portion of estimated frequencies is used to

fit the slope -α. The advantages of the introduced strategy can be seen in Figure 6a-d, which shows the same power spectra as shown in Figure 5a-d, but with the spectral slope -α now fitted over the lowest 50 frequencies. In contrast to Figure 5a-d, robust estimates of α are obtained regardless of sample rate.

Fitting over a fixed number of frequencies is notably different from fitting over a fixed percentage of frequencies. With regard to the high-frequency range, when the slope -α is fitted over the 25% of lowest frequencies, the high-frequency range of a power spectrum is treated equally regardless of the relative presence of spurious high-frequencies, and thus, regardless of sample rate. Specifically, the range of discarded frequencies (the frequencies at the right side of the x-axis of the power spectrum, ranging from highest fitted frequency to the highest estimated frequency, shown as a horizontal line in Figure 5a-d) remains equals across different sample rates. When the slope -α is fitted over the 50 lowest frequencies, as proposed here, the discarded frequency range changes as a function of sample rate. Specifically, as sample rate increases the range of discarded high-frequencies increases as well (hence, the horizontal line in Figure 6a-d). As a result, the range of discarded frequencies converges much more closely with the range of spurious frequencies.

With regard to the low-frequency range, fitting over the 25% of lowest frequencies implies fitting over a different low-frequency range for different sample rates. Specifically, relatively higher frequencies (hence, more biased frequencies) are incorporated in the fit as sample rate increases. For instance, in Figure 5a-d, the fitted frequencies range between 0 and 25 Hz, 0 and 12.5 Hz, 0 and 6.25 Hz, and 0 and 3.13 Hz for sample rates of 200, 100, 50, and 25Hz respectively. Fitting over the lowest 50 frequencies, in contrast, implies a fit over a stable low-frequency range, regardless of sample rate. Hence, in Fig. 6a-d, the cut-off frequency is the same; the slope -α is fitted between 0 and 0.31 Hz regardless of sample rate.

1.4. The present study

This paper examines the artifact in the estimation of 1/*f* noise parameters introduced by the choice of sample rate. We expect, based on previous observations (e.g., Carlini et al., 2002; Eke et al., 2002), that spurious information is introduced in the high-frequency range of the power spectrum as sample rate increases. We examine this artifact by comparing α exponents over a range of different sample rates using a variety of simulated and empirical time series. That is, we compare empirical or simulated data signals with their downsampled copies. In essence, downsampling is simply a post-hoc reduction in sampling rate by an integer factor. For a time series $x(n)$, when downsampling by the constant factor M, the downsampled copy *y(m)* may be represented as $y(m) = x(nM)$, where $y(m)$ is the downsampled sequence, obtained by taking every Mth sample from the original data sequence $x(n)$, thereby discarding $M - 1$ samples for every M samples. We expect that this post-hoc reduction in sample rate will effectively alter the spectral estimates for sampled data signals.

If increasing the sample rate has indeed the effect of reducing the amplitude of the signal at the highest frequencies, the overall estimated α exponent should increase as sample rate increases. In addition, the bias should not affect the low-frequency range of the power spectrum, and should become more pronounced when the spectral slope -α is fitted over a wider frequency range. This is investigated by fitting the spectral slope over 10, 25, or 100% of the lowest frequencies in the power spectrum. The outcomes are expected to be biased more strongly when the slope is fitted over 100% of the spectrum, and gradually become less biased as the slope is fitted over 25% (cf. Eke et al., 2002) and 10% (cf. Taqqu et al., 1995) of the lowest frequencies only. In contrast, when the slope is fitted over the lowest 50

frequencies only, and is thus fitted over a stable low-frequency range, with a stable cut-off frequency, it would be natural to expect the bias to be absent.

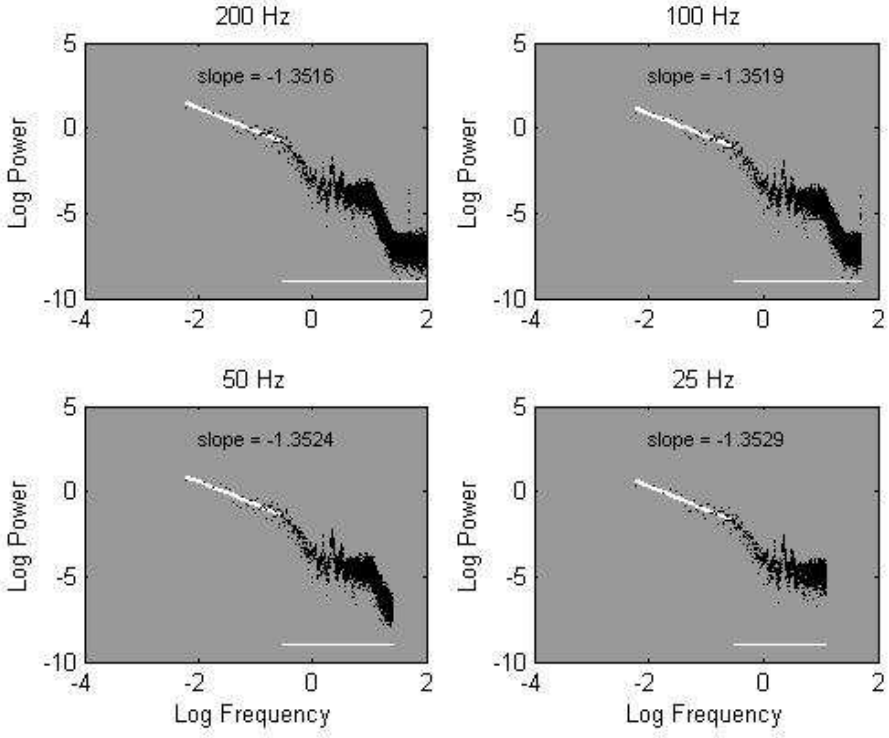

Figure 6. The same power spectra as shown in Fig. 5a-d, estimated from one Galvanic Skin Response time series sampled at 200Hz (a), 100Hz (b), 50Hz (c), and 25Hz (d). Spectral slopes are fitted over the lowest 50 of 2^{15} (a), 2^{14} (b), 2^{13} (c), and 2^{12} (d) estimated frequencies.

2. Downsampling

Method. The empirical data series have been collected in a precision aiming study. In the study, fifteen participants were invited to draw lines back and forth between two visual targets with a stylus, as fast and as accurately as possible. Participants received no instruction concerning pen pressure or pen tilt strategies. The targets were presented on a printed sheet of paper, one at the left side of the paper and one at the right side. The target width was 0.4 cm and the distance between targets was 24 cm. One block of 1100 trials was completed with the dominant hand. When the last trial was reached, a tone signaled the end of the experiment.

Pen pressure (in grams) and pen tilt (absolute deviation from the center of the stylus, in cm) coordinates were recorded using a digitizer tablet connected to a regular PC. The tablet samples at a temporal rate of 171Hz. In addition, a Galvanic Skin Response (GSR) signal was recorded on the finger tips of the non-moving hand at 200 Hz. Also, artificial 15 white noise signals ($1/f^0$), 15 $1/f$ noise signals ($1/f^1$), and 15 Brownian noise signals ($1/f^2$) were generated with a series length of 2^{16} data points, using an Inverse Fourier transform algorithm described by Lennon (2000).

After data collection, each time series was prepared to fit the needs for the spectral analysis (cf. Holden, 2005). First, outliers outside 3 * the standard deviation from the mean were removed. Next, because the Fourier transform fits stationary sines and cosines to the data series, simple drifts or long-term trends may distort the results. Linear and quadratic

detrending ensures that the analyzed data series is in line with the idealized mathematics of spectral analysis. Thus, linear and quadratic trends were removed for all data series (cf. Holden, 2005). Then, the original time series were normalized, and truncated by removing the data points at the beginning of the data series until 2^{16} data points were left. None of the empirical data series contained fewer then 2^{16} data values.

Next, the original data series (2^{16} data points) were downsampled by removing every next data point from the analysis, so that the new data series length was 2^{15}. This procedure was iterated until only 2^{10} data points were left, thereby reducing sample rate by a factor of 2^6. Then, for each of the resulting series, the spectral slope was either fitted over 10%, 25%, or 100% of the lowest frequencies, or over the 50 lowest frequencies.

3. Results and Discussion

The results from the pen pressure, pen tilt and Galvanic Skin Response data are shown in Figure 7a-c, which represents the fitted slope -α over a range of different sample rates for each data set. The different choices of fit are shown as separate lines in each Figure. It can be seen that regardless of the percentage of low frequencies used to fit the slope -α (10%, 25% or 100%), the observed α values effectively change in function of sample rate. As predicted, α exponents are higher at high sample rates. The artifact is most apparent when fitting the slope over the entire power spectrum and gradually becomes somewhat less dramatic as smaller portions of the low-frequencies are used to fit the spectral slope -α. When fitting over the 50 lowest frequencies however (shown as 50Low in Figure 7a-d), the slope -α remains robust against sample rate conversion.

Only the pen tilt data do not entirely confirm the expected artifact. At the highest sample rates, α values derived from a fit over the entire spectrum appear more robust than α values derived from a fit over the 10% or 25% lowest frequencies. But also in this example, α values derived from a fit over the 50 lowest frequencies constituted the most robust solution.

The simulated noise patterns, however, reveal a very distinct (hence, absent) effect of sample rate. The four choices of fit that were evaluated are shown in Figure 7d for each category of noise simultaneously. The random (α = 0), $1/f$ (α = 1) and Brownian (α = 2) noise simulations reveal robust values of α, regardless the choice of fit. This result confirms that the change in α arises from differences in sample density rather than from the differences in series length per se (with the 100% fit somewhat less reliable than the other choices of fit, however).

These results demonstrate that the relatively arbitrary choice of a sample rate dramatically alters the value of the α exponent if the spectral slope -α is fitted over a fixed percentage of low-frequencies. The bias is so strong that sample rate appears to be more influential on the estimated exponents than the process under scrutiny itself. This artifact is obviously problematic and leaves researchers with difficult decisions concerning the reliability of their

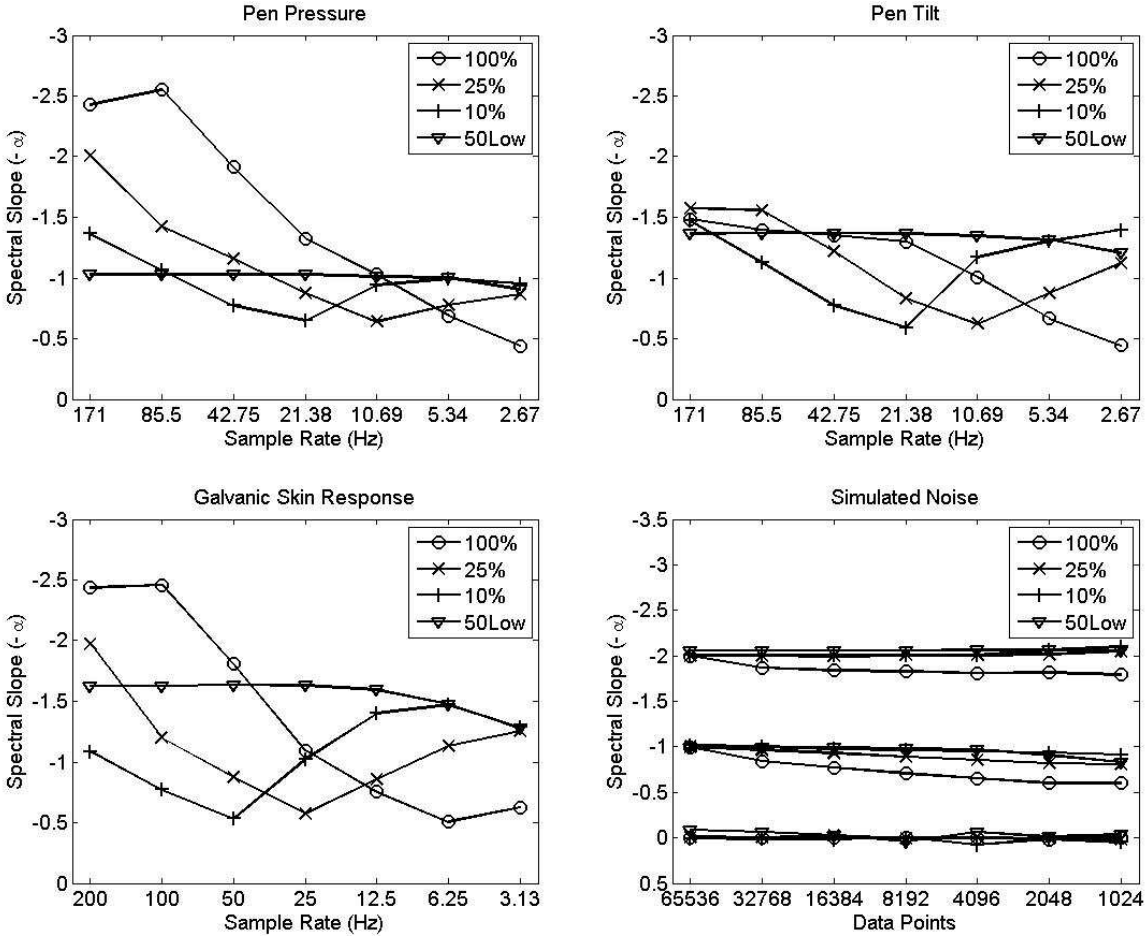

Figure 7. Average α scaling exponents from 15 pen pressure (a), pen tilt (b), Galvanic Skin Response (c), and simultated $1/f^0$, $1/f^1$, and $1/f^2$ data series (d) are shown on the y-axis. The x-axis shows sample rate for the empirical data series, and series length for the simulated series that also were downsampled by a factor of 2 in each step on the x-axis.

analysis. The strategy of spectral analysis introduced here results in scaling exponents that are robust against artifacts that come with dense sampling, and thus may solve those questions.

4. The sensitivity of α

A final confirmation of the introduced strategy for spectral analysis would require an evaluation of the sensitivity of the estimated exponents, in addition to their robustness against sample rate conversion. Sensitive exponents are more likely to differentiate among experimental conditions, and more clearly reveal the relation among different variables, given that such relations are present. In this case, we evaluate the correlation among different streams of $1/f$ noise (pen pressure and pen tilt) that were collected simultaneously in the previously introduced motor task.

The pattern of correlations between both streams of $1/f$ noise (pen pressure and pen tilt) shown in Figure 8 is remarkably heterogeneous over different sample rates, except for the strategy introduced here. α exponents estimated from the original, non-down-sampled data appear uncorrelated when relying on conventional spectral strategies. The correlations among pen pressure and pen tilt scaling exponents tend to grow stronger as sample rate decreases (hence, when fewer spurious high-frequencies are introduced in the analysis). The introduced

method for spectral analysis (shown as 50Low in Figure 8), in contrast, indicates strongly correlated streams of 1/*f* noise, regardless of sample rate.

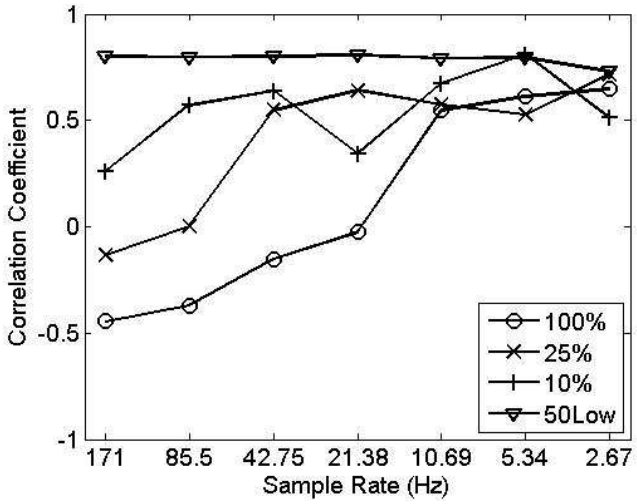

Figure 8. Correlation coefficients among α exponents estimated from pen pressure and pen tilt data (y-axis, N=15) over a range of sample rates (in Hz; x-axis) using different strategies for spectral analysis.

5. General Discussion

When spectral scaling exponents are estimated without anticipating artifacts introduced by sample rate, the exponent values themselves fluctuate widely across different sample rates. The order of magnitude of these discrepancies is dramatic: Scaling exponents may differ in magnitude by 1 or 2 depending on sample rate, while the order of magnitude of reliable differences in exponents between experimental groups and conditions are often in the range of .05 to .25 (e.g., Chen, Ding, & Kelso, 2001, Kello et al., 2007, Wijnants et al., 2009). These discrepancies may account for known inconsistencies in the psychological literature on 1/*f* noise, and perhaps, for the lack of a comprehensive framework of 1/*f* noise in continuous performance measures. Here we have introduced an empirical solution to this problem. The proposed strategy for spectral analysis is robust against changes in sample rate and renders more sensitive α exponents compared with more conventional strategies of analysis.

The artifact introduced in the high-frequency range of a power spectrum by differences in sample rate is not due to the inherent difference in data series length but is rather a natural consequence of the resulting differences in sample density. That is, denser sampling implies that the highest frequencies in a measured signal have lower amplitude compared with more sparsely sampled data. This artifact is important because it is implied that subtle methodological choices, often choices of convenience, may radically alter the outcome of spectral analysis when they are not adequately anticipated.

The proposed strategy for spectral analysis of continuous processes is to determine the spectral slope -α over a fixed amount (e.g., the 50 lowest frequencies), rather than a fixed percentage (10, 25, or 100%) of low-frequencies in a power spectrum. Fitting the slope over the 50 lowest frequencies, as suggested here, implies a fit over a different high-frequency range for different sample rates, but over a stable low-frequency range. Fitting the slope over a fixed percentage of lowest frequencies, however, implies a fit over a stable high-frequency range, but over a different low-frequency range. Given that the artifact introduced by sample

rate specifically concerns the high-frequency range of a power spectrum, it is obvious that the former strategy is to be preferred.

It might be informative to address explicitly that the discussion of applying spectral analysis to psychological data series was limited here to estimating the slope -α of the power spectrum in reliable and sensitive ways. In our suggested approach, we have followed the logic of Eke et al.'s (2002) recommendation to discard the highest frequencies and to focus on the lower frequencies. This recommendation is consistent with all example studies cited in the section '1/*f* noise in human performance'. In the section '1/*f* noise and periodic sampling', we acknowledged nonetheless that 1/*f* scaling relations often are observed within a finite range of scales only. The 1/*f* scaling relation may thus break down at specific frequency ranges, and usually at the highest frequencies.

Interestingly, this basic fact about power spectra of psychological data series has led some scientists to inquire whether low- and high frequency ranges in a power spectrum may represent the variability of different component mechanisms (Delignières, Torre, & Lemoine, 2008; Torre & Delignières, 2008). The scope of the present paper did not include an in depth discussion of that use of spectral analysis. The present evaluation of spectral analysis reveals no reason to believe that such uses of spectral analysis are problematic in any way when dealing with trial series or simulated data series. Yet, the cautious implication is that estimating high-frequency slopes is a rather delicate enterprise when confronted with time series sampled at arbitrary sample rates.

The present investigation may shed new light on known discrepancies in the literature on 1/*f* noise in psychological data. For instance, an explicit demonstration of such a discrepancy is described by Delignières, Torre, & Lemoine (2005) in the context of a study of relative phase in bimanual coordination. These authors estimated the scaling properties of *discrete* relative phase, corresponding to a cycle-to-cycle measurement yielding a trial series. The mean values of the estimated scaling exponent α ranged from 0.72 to 0.78, while *continuous* relative phase (hence, the same performance when treated as a time series), results in scaling exponents with an average value of about 2.52 (Schmidt, Beek, Treffner, & Turvey, 1991), far from the scaling range typically observed in trial series. This example confirms that different sampling regimes may effectively lead to appreciably different conclusions about the nature of the observed noise patterns.

Also within a similar sampling regime (i.e., when an across-study comparison yields only time series, rather than comparing time series with trial series) different results may be obtained with different choices of sampling. An example is provided by studies of postural sway. "Postural sway typically exhibits fractal scaling with exponents characteristic of fractional Brownian motion [*Brownian noise*] (cf. Collins & De Luca, 1993), although prolonged, unconstrained standing has suggested a pink [*1/f noise*] noise structure (Duarte & Zatsiorksky, 2001)" (Bonnet, Faugloire, Riley, Bardy, & Stoffregen, 2006, p. 806). These different results are methodologically interesting as well, if one notes that Collins and De Luca (1993) sampled their data at 100 Hz, while Duarte and Zatsiorksky (2001) sampled at 20 Hz. Here, we have shown that a comparison of these studies is only meaningful when the different sample rates of both experiments are taken into account, hence, when the scaling parameters are determined over an equivalent frequency range.

The ability to reliably and sensitively estimate scaling exponents, regardless of sample rate, and to compare these exponents (whether among different streams of 1/*f* noise, across

experimental conditions or across studies) is undoubtedly a requisite to achieve a coherent and comprehensive framework of 1/*f* noise in continuous processes. The present contribution might motivate an extension of the coherent framework of 1/*f* noise that has emerged for trial series of repeated discrete responses (e.g. Diniz et al., 2010; Van Orden, Kloos, & Wallot, 2011) to continuous performance measures.

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Chapter 6

Contemporary theories of 1/*f* noise in motor control

Based on:

Diniz, A., Wijnants, M. L., Torre, K., Barreiros, J., Crato, N., Bosman, A. M. T., Hasselman, F., Cox, R. F. A., Van Orden, G., & Delignières, D. (2011) Contemporary theories of 1/f noise in motor control. *Human Movement Science, 30,* 889-905. doi:10.1016/j.humov.2010.07.006

CHAPTER 6

Abstract

1/*f* noise has been discovered in a number of time series collected in psychological and behavioral experiments. This ubiquitous phenomenon has been ignored for a long time and classical models were not designed for accounting for these long-range correlations. The aim of this paper is to present and discuss contrasted theoretical perspectives on 1/*f* noise, in order to provide a comprehensive overview of current debates in this domain. In a first part, we propose a formal definition of the phenomenon of 1/*f* noise, and we present some commonly used methods for measuring long-range correlations in time series. In a second part, we develop a theoretical position that considers 1/*f* noise as the hallmark of system complexity. From this point of view, 1/*f* noise emerges from the coordination of the many elements that compose the system. In a third part, we present a theoretical counterpoint suggesting that 1/*f* noise could emerge from localized sources within the system. In conclusion, we try to draw some lines of reasoning for going beyond the opposition between these two approaches.

1. Introduction

1/*f* fluctuations present an intriguing phenomenon that received a growing interest in biology, psychology, and movement sciences during the last decade. This kind of fluctuation is typically observed during repeated performances of a given system, facing the same task in stable conditions for a prolonged period.

For a long time, variability was not *per se* considered a research interest for scientists. Attention focused on mean values, and their evolution with specific experimental conditions. Variability over successive trials was mainly conceived as the expression of methodological and experimental errors, or due to the presence of unmeaning noise in the system under study. Variability was generally discarded by means of averaging, over participants or trials, or by filtering in the case of time series. Sometimes, however, variability was considered a variable of interest, and was assessed in terms of magnitude through the calculation of variance, standard deviation, or coefficient of variation. These measures of variability implicitly suppose that fluctuations are white noise, i.e., uncorrelated over time.

Three decades ago, a growing interest for the analysis of dependencies in time series appeared, especially in econometrics (Box & Jenkins, 1976). This approach focused on short-term dependence, meaning that the current value is only dependent of the previous value, or of a few set of previous values. These hypotheses were particularly developed through the so-called ARMA models, containing auto-regressive or moving-average processes, in isolation or in combination (Box & Jenkins, 1976).

In most cases, however, correlations in the successive performances of the system are not restricted to the short-term, but are visible over various time scales. In other words, a typical dependence in the series, for example a positive trend between successive values, appears nested with similar trends expressing at larger scales. Statistically similar fluctuations are potentially observed at the level of the second, the hour, the day, the week, the year, and the century. As such, the current value possesses the “memory” of the entire preceding values of the series. This phenomenon was termed, alternatively, as long-term memory, long-range dependence, fractal process, or 1/*f* noise.

1/*f* noise has been discovered in a number of systems and in a number of situations. Such fluctuations have been found in heartbeat series (Peng et al., 1993), and in stride series during walking (Hausdorff et al., 1996). In the domain of experimental psychology, the seminal

paper of Gilden, Thornton, and Mallon (1995) evidencing the presence of 1/*f* fluctuations in tapping tasks had a great impact on the development of research in this area. 1/*f* noise was evidenced in subsequent experiment in various situations, including mental rotation, lexical decision, or visual search (Gilden, 2001), simple reaction time (Van Orden, Holden, & Turvey, 2003), forearm oscillation (Delignières et al., Lemoine, 2008), synchronization to a metronome (Chen, Ding, & Kelso, 1997; Torre & Delignières, 2008a), bimanual coordination (Torre, Delignières, & Lemoine, 2007), and serial force production (Wing, Daffertshofer, & Pressing, 2004). Delignières, Fortes, and Ninot (2004) evidenced 1/*f* fluctuations in the daily evolution of self-esteem.

The interest of scientists toward 1/*f* noise was reinforced by the discovery of the relationships between fractal fluctuations and health (Goldberger et al., 2002). 1/*f* fluctuations are generally evidenced in young and healthy systems, performing in a stable, unperturbed environment, and facing easy or overlearned tasks (Kello, Beltz, Holden, & Van Orden, 2007). In contrast, 1/*f* fluctuations seem to disappear with aging or disease (Hausdorff et al., 1997).

The aim of this paper is to present a general overview of current theories about 1/*f* noise, based on the contents of a symposium organized during the 2009' EWOMS congress in Lisbon. The first part of this paper develops a formal definition of 1/*f* noise, and presents the mathematical foundations of the methods used for evidencing the presence of such fluctuations and for measuring long-range correlations in the series. The second part introduces one of the prominent hypotheses in this domain of study, linking 1/*f* noise to the complexity of the system, and to the processes of coordination between their constituent self-systems. The third part presents an alternative point of view, suggesting that 1/*f* noise could take its origin in some specific sub-systems within the global system.

Note that the authors of this paper commit to different theoretical positions, and develop rather distinct, sometimes competing approaches of 1/*f* noise. We did not try to propose any kind of consensus between our points of view. We decided to present as clearly as possible the rationale of each theoretical position, in order to allow the reader to understand the meaning of the debate.

2. Formal mathematical definition of 1/*f* noise

An important issue in several scientific areas is the change of phenomena over time. The classical methods of analysis are based on descriptive statistics, such as the mean and the variance, and ignore the dimension of time. In contrast, the time series methods, in the so-called time and frequency domains, focus on the dynamical behaviors across time and allow for modeling and inference. In the biological field, numerous studies have revealed results typical of a particular type of structure called long-term memory or long-range dependence. To assess the fundamental properties of the observed signals, it is natural to consider that they are realizations of stochastic processes. For the signals under study, it is usually supposed that they have a kind of stability that can reasonably be modeled by stationary processes.

In the time domain analysis, a central concept is the autocorrelation function of the process which gives the correlation between variables of the process at two different times. Formally, a stochastic process is said to be stationary (in the wide sense) if its mean is constant across time and its autocorrelation function depends only on the time lag between the variables. In this case, the stochastic memory of the process can be defined as the speed of the decay of the autocorrelation function. Formally, a stationary process is said to have long memory if its autocorrelation function $\rho(.)$ satisfies the power law

$$\rho(k) \sim c\, k^{-(1-2d)},\ k \to \infty, \tag{1}$$

where c and d are two constants such that $c \neq 0$, $d \neq 0$, and $d < 0.5$, and k is the lag. This means that the function $\rho(.)$ decays to zero very slowly with a hyperbolic decay. Moreover, the process is said to have persistent long memory if $0 < d < 0.5$, so that $\Sigma_{k=-\infty}^{\infty} \rho(k) = \infty$, reflecting the fact that the remote past has a strong influence into the present.

In the frequency domain analysis, a key concept is the spectral density function of the process which gives the amount of variance accounted for by each frequency in the process and corresponds mathematically to the Fourier transform of the autocorrelation function. The spectral density function allows for identifying dominant frequencies in the process that may be associated to hidden periodicities. Formally, a long-memory process can be defined as a process whose spectral density function $S(.)$ satisfies the power law

$$S(f) \sim c\, f^{-2d},\ f \to 0, \tag{2}$$

where c and d are two constants such that $c \neq 0$, $d \neq 0$, and $d < 0.5$, and f is the frequency. This means that the function $S(.)$ has a pole at zero if $0 < d < 0.5$, that is $S(0) = \infty$, signifying that the low frequencies predominate and therefore long-term oscillations are expected. These processes whose function $S(.)$ has the form $S(f) \sim f^{-\alpha}$, where $\alpha = 2d$ and so α is a constant such that $\alpha < 1$, are usually known as $1/f^{\alpha}$ noise. Note that the definitions in Eq. (1) and (2) are mathematically equivalent.

In continuous time, a long-memory process is self-similar. Formally, a stochastic process $\{Y_t\}$ is said to be self-similar with parameter H if, for any constant $c > 0$, it satisfies the relation

$$Y_{ct} =_d c^H Y_t,\ t \in \mathrm{R}, \tag{3}$$

where $=_d$ denotes equality in distribution. This means that the process $\{Y_t\}$ has identical statistical properties independent of the scale of observation. For a long-memory process, the parameter H relates to the parameter d through the expression

$$H = d + 0.5 \tag{4}$$

In conclusion, a long-memory process has special properties, in the time and in the frequency domains, which are very distinct from those of other traditional stationary processes. Apart from the definitions of long memory presented here, there are other possible definitions. Some interesting details can be found in Baillie (1996) and Guégan (2005).

3. Some methods for the detection and estimation of exponents

Many methods, in the time and in the frequency domains, have been proposed to estimate the long-memory and the self-similarity parameters d and H (e.g., Eke, Herman, Kocsis, & Kozak, 2002). Among these methods, there are some heuristic techniques, non- or semi-parametric, mainly useful as first diagnostic tools for checking the existence of long memory, and more refined techniques, parametric and model-dependent, useful for estimating the long-memory and the scale parameters. For reference, four methods are presented below, namely the rescaled range methodology (R/S), the detrended fluctuation analysis (DFA), the Geweke and Porter-Hudak regression (GPH), and the maximum likelihood estimation (MLE). These methods have been widely used in the literature and provide suitable and complementary tools for the study of long-memory time series.

The R/S method was initially developed by Hurst (1951) in a study of the levels of the Nile River and it was explained by Mandelbrot (1965) with the introduction of fractional models.

This method is one of the better known methods and it is based on the rescaled adjusted range. For a time series $\{Y_1,\ldots,Y_n\}$ and a positive integer $n_s \leq n$, the R/S statistic is defined as

$$Q(n_s) = R(n_s)/S(n_s), \tag{5}$$

with

$$R(n_s) = \max_{1\leq r\leq n_s} \sum_{t=1}^{r} (Y_t - \overline{Y}) - \min_{1\leq r\leq n_s} \sum_{t=1}^{r} (Y_t - \overline{Y}) \tag{6}$$

and

$$S(n_s) = [\sum_{t=1}^{ns} (Y_t - \overline{Y})^2/n_s]^{1/2}, \tag{7}$$

where $\overline{Y}$ is the sample mean. This signifies that the statistic $Q(.)$ records the integrated series range adjusted for the mean and normalized by the standard deviation in blocks of length n_s.

For a persistent long-memory process, the statistic $Q(.)$ satisfies the power law

$$E[Q(n_s)] \sim c\, n_s^b, \;\; n_s \to \infty, \tag{8}$$

or, equivalently,

$$\log E[Q(n_s)] \sim \log c + b \log n_s, \;\; n_s \to \infty, \tag{9}$$

where c and b are two constants such that $c > 0$ and $0.5 < b < 1$ (for short-memory, $b = 0.5$). The parameter b is called the Hurst exponent or the self-similarity parameter H.

To estimate H through the R/S method, proceed as follows: (i) divide the time series of length n into contiguous blocks of length n_s with starting points $p_j = (j - 1)\, n_s + 1$, $j = 1,\ldots, [n/n_s]$; (ii) compute, for each block, the value of $Q(n_s)$ and determine the mean $\overline{Q}\,(n_s)$. Then, repeat this procedure over all possible block lengths n_s (in practice, $10 \leq n_s \leq [n/2]$) and plot $\log \overline{Q}\,(n_s)$ against $\log n_s$. Finally, fit a linear-regression model to the points, obtain the slope $\hat{b}$ with a least-squares method, and set $\hat{H} = \hat{b}$ (Taqqu, Teverovsky, & Willinger, 1995; Delignières, Torre, & Lemoine, 2005).

The DFA method was established by Peng et al. (1993) in a study of the behavior of the heartbeat. This method is based on the detrended values fluctuation. For a time series $\{Y_1,\ldots,Y_n\}$ and a positive integer $n_s \leq n$, the DFA statistic is given by

$$F(n_s) = [\sum_{r=1}^{n} [W_r - \hat{W}_r\,(n_s)]^2/n]^{1/2}, \tag{10}$$

with

$$W_r = \sum_{t=1}^{r} (Y_t - \overline{Y}) \quad \text{and} \quad \hat{W}_r\,(n_s) = \hat{a}_0\,(n_s) + \hat{b}_0\,(n_s)\, r, \qquad r = 1,\ldots,n, \tag{11}$$

where $\overline{Y}$ is the sample mean, $\hat{a}_0\,(n_s)$ and $\hat{b}_0\,(n_s)$ are the integrated series estimators of the coefficients of linear-regression models. This signifies that the statistic $F(.)$ records the integrated series variability adjusted for local trends in blocks of length n_s.

For a persistent long-memory process, the statistic $F(.)$ satisfies the power law

$$E[F(n_s)] \sim c\, n_s^b, \;\; n_s \to \infty, \tag{12}$$

or, equivalently,

$$\log E[F(n_s)] \sim \log c + b \log n_s, \;\; n_s \to \infty, \tag{13}$$

where c and b are two constants such that $c > 0$ and $0.5 < b < 1$ (for short-memory, $b = 0.5$). The parameter b is the self-similarity parameter H.

To estimate H through the DFA method, proceed as follows: (i) divide the time series of length n into contiguous blocks of length n_s with starting points $p_j = (j - 1)\, n_s + 1$, $j = 1,\ldots, [n/n_s]$; (ii) compute, for the length n_s, the value of $F(n_s)$. Then, repeat this procedure over all possible block lengths n_s (in practice, $10 \leq n_s \leq [n/2]$) and plot $\log F(n_s)$ against $\log n_s$. Finally, fit a linear-regression model to the points, obtain the slope $\hat{b}$ with a least-squares method, and set $\hat{H} = \hat{b}$ (Taqqu et al., 1995; Delignières et al., 2005).

The GPH regression was introduced by Geweke and Porter-Hudak (1983). This method involves a regression of the logarithm of the periodogram on the logarithm of a function of the frequency. Recall that, for a time series $\{Y_1,\ldots,Y_n\}$, the periodogram $I(.)$ is defined as

$$I(f_j) = |\textstyle\sum_{t=1}^{n} Y_t\ e^{-itf_j}|^2/(2\pi n),\ \ f_j = (2\pi j)/n,\ \ j = 1,\ldots, [n/2], \tag{14}$$

where $I(f_j)$ represents the intensity of the frequency f_j. It is well know that the periodogram is an estimator of the spectral density function (Brockwell & Davis, 1991).

For a persistent long-memory process, the spectral density function $S(.)$ satisfies the relation

$$S(f) = S^*(f)\, |1 - e^{-if}|^{2b},\ \ |f| \leq \pi \quad (S(f) \sim c\, f^{2b},\ \ f \to 0), \tag{15}$$

where $S^*(.)$ is an even function that is finite and nonzero at zero, and b is a constant such that $b = -d$ and $0 < d < 0.5$, that is, b is the negative of the long-memory parameter d (for short-memory, $b = 0$ and $d = 0$); the periodogram $I(.)$ satisfies the relation

$$\log I(f_j) = a + b \log |1 - e^{-if_j}|^2 + e_j,\ \ f_j \approx 0,\ \ j = 1,\ldots,m, \tag{16}$$

where a and b are two constants such that $b = -d$ and $0 < d < 0.5$, e_j are independent and identically distributed random variables, and $m = [n^{0.5}]$.

To estimate d through the GPH method, compute the values of $I(f_j)$ and plot $\log I(f_j)$ against $\log |1 - e^{-if_j}|^2$. Then, fit a linear-regression model to the points, obtain the slope $\hat{b}$ with a least-squares method, and set $\hat{d} = -\hat{b}$ (Taqqu et al., 1995; Crato & Ray, 2000). The power spectral density method (PSD) is very similar to this method but it is based on the asymptotic distribution of the spectral density function instead of the exact distribution shown in Eq. (15) (Delignières et al., 2005).

The maximum likelihood methods, in the time and in the frequency domains, are based on parametric models and allow for the estimation of the long-memory parameter as well as scale parameters. Suppose that $\{Y_t\}$ is a Gaussian stationary process with mean $\mu = 0$ and autocovariance function $\gamma(.)$ whose model comes from a parametric family with parameter vector $\boldsymbol{\beta}$. Suppose, in addition, that $\mathbf{Y}_n = (Y_1,\ldots, Y_n)'$ is a realization of the process with covariance matrix $\Gamma_n(\boldsymbol{\beta}) = [\gamma(i-j)]_{i,j=1,\ldots,n}$. Then the likelihood function is equal to

$$L_n(\boldsymbol{\beta}) = (2\pi)^{-n/2}\, [\det \Gamma_n(\boldsymbol{\beta})]^{-1/2} \exp[-1/2\ \mathbf{Y}_n'\, \Gamma_n^{-1}(\boldsymbol{\beta})\, \mathbf{Y}_n] \tag{17}$$

and the log-likelihood function is equal to

$$\log L_n(\boldsymbol{\beta}) = -n/2 \log 2\pi - 1/2 \log \det \Gamma_n(\boldsymbol{\beta}) - 1/2\ \mathbf{Y}_n'\, \Gamma_n^{-1}(\boldsymbol{\beta})\, \mathbf{Y}_n. \tag{18}$$

The maximum likelihood estimator of $\boldsymbol{\beta}$ is obtained by maximizing $L_n(\boldsymbol{\beta})$ or $\log L_n(\boldsymbol{\beta})$ with respect to $\boldsymbol{\beta}$. However, the maximization of $L_n(\boldsymbol{\beta})$ or $\log L_n(\boldsymbol{\beta})$ requires the calculation of the determinant and the inverse of the matrix $\Gamma_n(\boldsymbol{\beta})$ which can pose computational problems, in particular for long time series with long memory. These problems can be minimized with some analytical algorithms, such as the Durbin-Levinson algorithm (Durbin, 1960).

An alternative to maximizing the exact likelihood function in the time domain is to maximize an approximation to that function in the frequency domain. Suppose that $S(.;\boldsymbol{\beta})$ is the spectral

density function of the process, $I(.)$ is the periodogram of the realization, and $f_j = (2\pi j)/n$. With some approximations proposed by Whittle (1953) and some Riemann sums, the negative of the log-likelihood function is approximated up to a constant by

$$\mathcal{L}_n(\boldsymbol{\beta}) = \sum_{j=1}^{[n/2]} \log S(f_j;\boldsymbol{\beta})\ 2/\mathrm{n} + \sum_{j=1}^{[n/2]} I(f_j)/S(f_j;\boldsymbol{\beta})\ 2/\mathrm{n}. \qquad (19)$$

The approximate maximum likelihood estimator of $\boldsymbol{\beta}$ is obtained by minimizing $\mathcal{L}_n(\boldsymbol{\beta})$ with respect to $\boldsymbol{\beta}$. When it is not easy to specify a parametric model and a spectral density function for the observations, it is possible to use a similar semi-parametric method for estimating the parameters of interest as long as the shape of the spectral density is known (Robinson, 1995). Thus, this is a very flexible method which can be used even in additive models widely found in motor control theories (Diniz, Barreiros, & Crato, 2010).

In sum, there are various methods to estimate the long-memory and the self-similarity parameters. The heuristic techniques are based on specific properties of the time series, whereas the maximum likelihood type techniques are based on parametric models. The methods reviewed here are some of the most widely used in the estimation of the parameters. Some additional techniques can be seen in Taqqu et al. (1995) and Delignières et al. (2005).

4. Looking at 1/*f* noise as a signature of system complexity

The origin of 1/*f* noise in the behavior of biological systems remains an issue of debate across scientific disciplines. The differences in approach that feed the debate, as in the current article, are partially due to the fact that a number of different mechanisms are able to effectively produce 1/*f* noise in system dynamics (i.e., both simple and complex systems). Complex systems are systems that consist of a set of interrelated and interdependent parts with an almost infinite amount of degrees-of-freedom that cohere into a coordinated functional system. The parts dynamically interact in nonlinear ways, a conceptual metaphor referred to as interaction dominance (e.g., Van Orden et al., 2003). Defining features include self-organization (the spontaneous organization that coordinates system behavior in the absence of a central controller) and emergence (the appearance of features that are not implicit in the parts of the system). On the other hand, simple systems are systems that contain a number of distinct components whose internal dynamics, when integrated, account for the observed performance. This way of thinking is the more conventional conceptual metaphor to think about movement control and may be referred to as component dominance because “the intrinsic activities of the components are held to be much more dominant in determining the observed performance than the interactions among components” (Turvey, 2007, p. 690).

Some theorists attempt to compromise between these approaches. For example, Delignières and colleagues (see Section 5.) commit to the idea of local interactions as a mechanism underlying 1/*f* noise, without committing to the idea of multiplicative interactions among components. Delignières et al. rather conceive such local interactions as within-component coordination dynamics. In this section, Van Orden and colleagues argue that the widely observed 1/*f* noise in human behavior is the fingerprint of a complex system in the true physical sense; that is, a system comprising fully interdependent feedback processes among components (e.g., Turvey, 2007). Accepting this premise, 1/*f* noise necessarily results from the intrinsic dynamics that govern human behavior (Kello et al., 2007; Van Orden et al., 2003; Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009a). Accepting the origin of 1/*f* noise in complexity, it may be postulated that, far from being mere noise, 1/*f* noise is actually the signature of strongly emergent coordination (e.g., Buzsaki, 2006; Kello et al., 2007; Van

Orden et al., 2003; Wijnants et al., 2009a). This general hypothesis is illustrated in the five predictions listed next, to evaluate 1/*f* noise as a metric for coordination in human behavior.

4.1. 1/f noise is ubiquitous in human performance.

Any behavioral phenomenon will reveal long-range dependence if measured over a sufficient duration in time (usually 2^{10} data points suffice, Delignières, Lemoine, & Torre, 2004). If 1/*f* noise originates from a complex system, any component process stems from the mutual interactions that govern the system. The implication is that any process should yield 1/*f* noise in its dynamics. To date, dozens of studies have been published on long-range dependence in cognitive and motor performance, all demonstrating widespread, perhaps ubiquitous 1/*f* noise (e.g., Kello et al., 2007; Van Orden, Kloos, & Wallot, 2010, are reviews).

4.2. 1/f noise is obscured when sources of external variation are increased.

Intrinsic fluctuations which govern the cognitive system are obscured when external variation in an experiment increases. For example, external manipulations of task demands may constitute sources of white noise. Such random perturbations to behavior caused by external factors disrupt the intrinsic dynamics, thereby obscuring their signature. Thus, unsystematic changes across trial measurements show themselves as "whitened" signals of 1/*f* noise, as they reduce the presence of 1/*f* noise in the now de-correlated behavioral signal (e.g., Clayton & Frey, 1997; Correll, 2008). Conversely, when unsystematic sources of external perturbation are minimized, white noise is reduced and 1/*f* noise is more clearly present (e.g., Kello, Beltz et al.; Kiefer, Riley, Shockley, Villard, & Van Orden, 2009, Ward & Richard, 2001). This prediction stems from the broad association between 1/*f* noise and intentionality (Van Orden et al., 2003): Adding external constraints reduces the demands for voluntary control and the presence of 1/*f* noise in a behavioral signal, resulting in a whitened signal, regardless of the specificity of a certain task.

Also more systematic trial-by-trial perturbations reduce the presence of 1/*f* noise. For example, providing feedback in a time estimation task constrains responding sufficiently to reduce demands for voluntary control and a whitened signal is the result (Kuznetsov, 2009). Similarly, entrainment reduces the need for voluntary control and also whitens behavioral signals. In continuation tapping participants tap in synch to a training beat and then tap from memory after the metronome is turned off. Leaving the metronome on throughout cedes control of tapping to the environment via entrainment, which reduces the demands of voluntary control and consequently reduces the presence of 1/*f* noise in the asynchronies to the metronome. A whiter signal is observed in entrained signals compared to continuation tapping and compared to a control condition of syncopated tapping between the beats (Chen, Ding, & Kelso, 2001; see also Hausdorff et al., 1996).

Following this logic, one may expect clearer signals of 1/*f* noise in tasks that emphasize voluntary control, such as measurement trials that do not include a response cue. For example, in tasks like precision aiming or spatial and temporal estimation, the "stimuli" (targets) remain in front of the participant throughout the task and one sees clear signals of 1/*f* noise (Gilden et al., 1995; Wijnants et al., 2009a) compared to simple response or word-naming tasks (Van Orden et al., 2003) which do include a response cue at each trial. Hence, the presence of 1/*f* noise changes in predictable ways across tasks as a function of external constraints, a finding which seems to require a domain-general explanation.

4.3. More stable and coordinated behaviors reveal a clearer 1/f noise signature.

The premise that the behavior of a complex system is determined by the interactions among components leads to the prediction that these interactions are more apparent in the intrinsic dynamics of the system, if the system operates in more coordinated and efficient ways. This prediction is in line with results obtained in other disciplines: 1/*f* noise in living systems is generally accepted as an emergent pattern of coordination (West & Brown, 2005).

For instance, physiological systems reveal healthy and coordinated functioning in the presence of 1/*f* noise. When a human heart deviates from 1/*f* noise in an inter-beat interval sequence, in either the direction of randomness (white noise) or over-regularity (brown noise), this deviation from the adaptive healthy baseline indicates pathological, life-threatening states like atrial fibrillation and congestive heart failure, respectively (Goldberger, 1996; Goldberger et al., 2002; Havlin et al., 1999). The clear relation between complexity and coordination is not unique to heart beat dynamics. Other examples include epilepsy, fetal distress syndrome, major-depressive disorder, attention deficit and hyperactivity disorder, falling, and slow transit constipation, among others (Goldberger, 1996; Linkenkaer-Hansen et al., 2005; Hausdorff, 2007; Gilden & Hancock, 2007; Yan, Yan, Zhang, & Wang, 2008); all of which are associated with a deviation from the healthy fractal pattern of 1/*f* noise.

The issue of coordination in physiological processes parallels the coordination of motor behavior. For instance, 1/*f* noise is less prominent in stride intervals of human gait with disease. Both Huntington's and Parkinson's Disease patients reveal reliably more randomness and less 1/*f* noise in the time series collected from their gait cycles compared to healthy controls (Hausdorff, 2007). Furthermore, 1/*f* noise is strongly correlated with the severity of the illness.

If more stable and coordinated behaviors are associated with the clearer presence of 1/*f* noise, one would expect that 1/*f* noise emerges less clearly in more challenging tasks. There is some evidence suggesting that more effortful task conditions indeed reduce the presence of 1/*f* noise (Clayton & Frey, 1997; Correll, 2008). Likewise, one may expect that 1/*f* noise emerges more clearly as task performance improves with learning. For example, extensive practice of a motor task yields a reduced signal of white noise and an enhanced signal of 1/*f* noise (Wijnants et al., 2009a). Wijnants et al. (2009b) successfully replicated this finding in a different domain; word-naming. The study was based on the robust observation that word repetition facilitates word-naming performance. When word stimuli are named repeatedly (over three identical blocks), again 1/*f* noise emerged more clearly over blocks of practice.

From an interaction-dominant perspective, it is argued specifically that the discussed association of 1/*f* noise and coordination processes is too general to be captured by task-specific explanations. These findings rather seem to suggest a broad connection between 1/*f* noise and the self-organization across processes of mind and body (Van Orden et al., 2010).

4.4. 1/f noise should be accompanied by additional evidence for emergence and self-organization.

If the relation between 1/*f* noise and coordination can be understood as the coupling or interdependence of components, as opposed to their independence, 1/*f* noise should covary with other dynamical measures. Examples include reduced entropy, a decrease in system dimensionality and a more efficient recycling of kinetic energy in sequences of rhythmical movement (e.g., Wijnants et al., 2009a; Wijnants et al., 2010). We may expect additional surprises in this vein if we truly confront interaction-dominant dynamics and complexity (e.g., Ihlen & Vereijken, in press). Altogether, such system properties may support or reject the

postulation that the relative presence of 1/*f* noise constitutes a sensitive metric for emergent coordination. Unfortunately, in most studies that incorporate 1/*f* noise, other dynamical measures are not evaluated. However, it is exactly the convergence between such measures, which reveals the full-blown complexity of the cognitive system, thereby posing specific challenges to the development of contemporary theories and models of motor control.

Note that fractal methods do not replace traditional measures based on means and standard deviations, because they provide orthogonal and complementary pieces of information about the behavior of the system. Several studies suggest, however, that 1/*f* may constitute a more sensitive metric compared to measures of central tendency to discriminate between groups and experimental manipulations (Anderson, Lowen, & Renshaw, 2006; Hausdorff, 2007; Kiefer et al., 2009).

4.5. Indefinite numbers of 1/f signals exist in any behavior.

According to the premise, 1/*f* noise is a generic property of system interactions that give rise to all behaviors. According to emergent coordination, 1/*f* noise is not restricted to some domain-specific process or measure of cognition. Any and all behavioral signals should yield 1/*f* noise under conditions of intrinsic fluctuation, even if there are multiple distinct signals. Thus, one should be able to find multiple, parallel streams of 1/*f* noise under conditions of intrinsic fluctuation. Kello, Anderson, Holden, and Van Orden (2008) instructed participants to repeat an utterance (here, the word bucket) many times in order to elicit intrinsic fluctuations from one utterance to the next. The authors took over 100 acoustic measures of each word utterance and analyzed the fluctuations in those measures from one *bucket* to the next. Every single measure was found to fluctuate as 1/*f* noise, including dozens of parallel yet uncorrelated 1/*f* fluctuations. The findings of 1/*f* noise throughout the intrinsic fluctuations of speech, and in two different key response measures (Kello et al., 2007), are parsimoniously explained by emergent coordination: 1/*f* noise is prevalent wherever intrinsic fluctuations are measured. Does each signal require its own mechanism?

5. An alternative hypothesis: ‘localized’ sources of 1/*f* noise

The preceding part of this paper develops a strong theoretical point of view, considering 1/*f* fluctuations as the natural expression of coordination within complex systems (Kello et al., 2008; Kello et al., 2007; Van Orden et al., 2003, 2005). According to this point of view, 1/*f* noise is related to very general properties of complex systems, such as self-organized criticality and metastability. These properties are supposed to express in all complex systems, and as such provide a satisfying explanation for the ubiquity of 1/*f* noise. The authors contest the necessity of domain-specific hypotheses for fractal fluctuations: as claimed by Kello et al. (2007), “1/*f* scaling [noise] is too pervasive to be idiosyncratic” (p. 551). As a consequence, the authors oppose the idea of a structural localization of 1/*f* sources within the system: “Pink [1/*f*] noise cannot be encapsulated; it is not the product of a particular component of the mind or body. It appears to illustrate something general about human behavior” (Van Orden et al., 2003, p. 345). This so-called *nomothetic perspective* to 1/*f* noise (Torre & Wagenmakers, 2009) seeks for general explanations, regardless of the specificity of any hypothesized subsystem.

Torre, Delignières, and collaborators adopted a different point of view (Delignières et al., 2004; Delignières et al., 2008; Delignières & Torre, 2009; Torre & Delignières, 2008a, 2008b; Torre & Wagenmakers, 2009). The main specificity of their approach is to combine the analysis of fractal, long-range correlations, with that of short-term dependence in the series.

Their work initiated in the study of timing tasks, and especially finger tapping. The finger tapping task has a long history in experimental psychology. In the most basic experimental condition, participants are instructed, after a short period during which a metronome provides a given tempo, to continue tapping following the same rhythm despite the removing of the metronome. The most famous model for this so-called 'continuation' condition was proposed by Wing and Kristofferson (WK model, 1973). This model is composed of two components: a cognitive timekeeper that generates series of time intervals C_i, and a motor implementation process in charge of the execution of the tap at the end of each interval. The motor component is supposed to present a delay M_i. According to this model, the produced inter-tap interval is given by the period provided by the timekeeper, plus the difference between the time delays that characterize the two taps that limit the interval:

$$I_i = C_i + M_i - M_{i-1}. \quad (20)$$

In the initial formulation of the model, C_i and M_i were both considered as uncorrelated white noises. This model especially allowed to account for the typical negative lag-one autocorrelation in inter-tap interval series (due to the presence of the same M_i term, but of opposite signs, in successive inter-tap intervals).

Gilden et al. (1995) applied spectral analysis to prolonged series of inter-tap intervals, and showed that the log-log power spectrum presented a negative linear trend in the low-frequency region, indicative of 1/*f* noise, and a positive trend in the high-frequency region. This result was confirmed by a number of subsequent studies (Delignières et al., 2004; Lemoine, Delignières, & Torre, 2006; M. Yamada, 1996; N. Yamada, 1995; Yamada & Yonera, 2001; Yoshinaga, Miyazima, & Mitake, 2000; see Figure 1). According to Gilden et al. (1995), the positive slope in high frequencies is typical of differenced white noise, and thus, can be attributed to the $M_i - M_{i-1}$ part of the WK model. The authors concluded that the timekeeper C_i should be a 1/*f* source, responsible of the fractal fluctuations in inter-tap interval series. They finally stated that the cognitive component should be considered a complex dynamical system, composed of multiple interacting components. Note that in contrast with the basic assumptions of Van Orden, Kello, and their collaborators, Gilden's approach suggested that the source of 1/*f* noise could be "localized" within the global system, in a sub-system that interacts with other components for producing the final outcome.

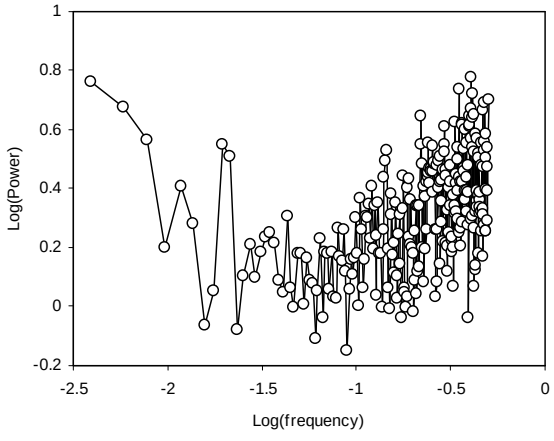

Figure 1. Log-log power spectrum of series of inter-tap intervals in continuation finger tapping (Delignières et al., 2008). This average spectrum presents a negative slope in the low- frequency region, indicative of 1/*f* noise, and a positive slope in high frequencies typical of differenced white noise.

A second aspect of the tapping paradigm consists of asking participants to tap in synchrony with the sounds emitted by a metronome. This experimental condition allows collecting two variables: the series of inter-tap intervals, and the series of asynchronies to the metronome. Chen et al. (1997) showed that the series of inter-tap intervals, in synchronization tapping, were no more 1/*f* noise, but were negatively correlated. In contrast, they discovered 1/*f* fluctuations in the series of asynchronies to the metronome (see Figure 2). Surprisingly, Chen et al. did not try to relate the finding of 1/*f* noise in asynchronies in their experiment with the presence of fractal fluctuations in inter-tap intervals in continuation, as evidenced by Gilden et al. (1995). They considered that synchronization could *per se* induce 1/*f* noise, as the natural outcome of the complex system formed by experimental constraints. They proposed that complex systems could be characterized by "essential variables" (e.g., asynchronies in synchronization tapping), and that 1/*f* fluctuations appeared at the level of these essential variables. This proposition is consistent with the nomothetic approach of Kello, Van Orden, and collaborators: each experimental condition is supposed to establish a new set of constraints, determining a complex system that expresses itself in time through 1/*f* fluctuations. From this point of view, however, the presence of 1/*f* noise in periods in continuation tapping, and in asynchronies in synchronization tapping are just independent phenomena.

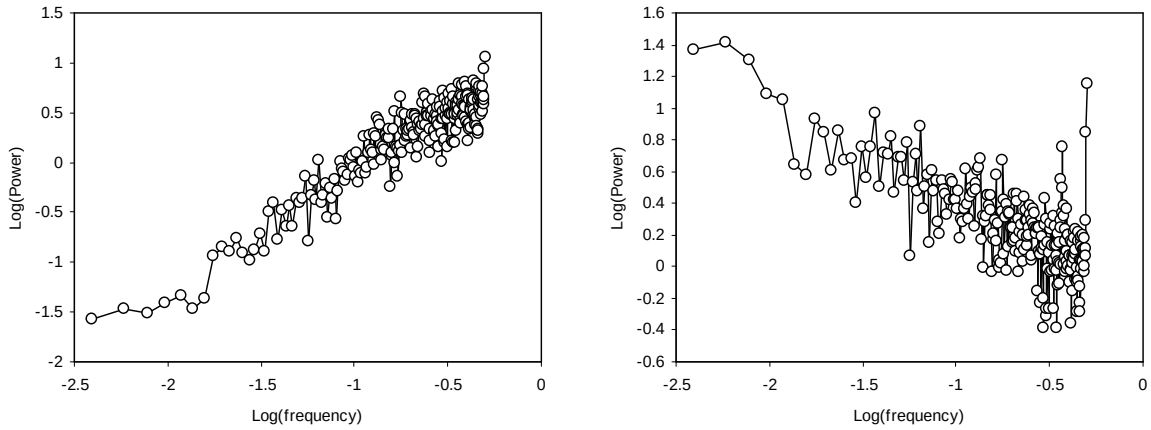

Figure 2. Log-log power spectra of series of inter-tap intervals (left) and asynchronies (right), in synchronization finger tapping (Torre and Delignières, 2008a). The positive slope, for inter-tap interval series, reveals the presence of negative serial correlations between successive values. The negative slope for asynchronies series is indicative of the presence of 1/f noise.

In contrast, Torre and Delignières (2008a) proposed a unifying framework to account for the presence of 1/*f* fluctuations in both continuation and synchronization tapping. They started from the linear phase correction model proposed by Vorberg and Wing (1996). We first present the rationale of this model.

In synchronization tapping, each inter-tap interval (I_i) corresponds to the difference between its previous and next asynchronies (A_{i-1} and A_i), plus the period (τ) imposed by the metronome:

$$I_i = A_i - A_{i-1} + \tau. \tag{21}$$

The main assumption of the model is that the preceding asynchrony is taken into account by a linear phase correction: The interval produced by the timekeeper is corrected by a fraction of the preceding asynchrony:

$$C^*_i = C_i - \alpha A_{i-1}. \quad (22)$$

As proposed in the WK model, the produced interval results from the combination of this corrected cognitive interval and the two successive motor delays:

$$I_i = C^*_i + (M_i - M_{i-1}). \quad (23)$$

Combining Eq. (21), (22), and (23) leads to the following expression for current asynchrony:

$$A_i = (1 - \alpha)A_{i-1} + C_i + (M_i - M_{i-1}) - \tau. \quad (24)$$

The strength of this model is to offer a unifying framework for continuation and synchronization tasks: the Vorberg-Wing model is an extension of the basic WK model for continuation, and both models include the timekeeper entity initially postulated by Wing and Kristofferson (1973). As such, a timekeeper possessing fractal properties could explain the presence of fractal correlations in inter-tap interval series in continuation on the one hand, and in asynchrony series in synchronization on the other hand. Indeed, Torre and Delignières (2008a) proposed to enrich the Vorberg and Wing (1996)'s model by providing C_i with fractal properties, and showed that this "1/*f*-linear phase correction model" was able to adequately reproduce the complex correlation structures of period and asynchrony series. The most important, at this point, is to note that the WK model (Eq. (20)) and the Vorberg-Wing model (Eq. (24)) are able to account for the complex patterns of serial correlations in continuation and synchronization tapping, respectively, from the moment that a single element in both models is provided with fractal properties.

A similar approach was developed for another kind of rhythmic task: forearm oscillations. In a first step, Delignières et al. (2004) applied spectral analysis to series of periods collected during self-paced oscillations. Results showed that, like in tapping, period series presented 1/*f* fluctuations with a negative linear slope in the low-frequency region of the log-log spectrum. In the high-frequency region, in contrast, the authors observed a simple flattening of the log-log spectrum, the slope remaining slightly negative (see Figure 3).

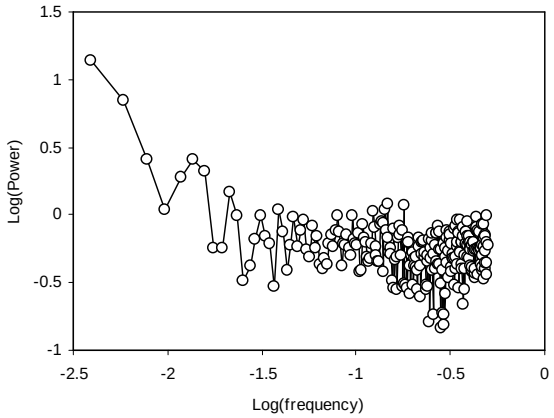

Figure 3. Log-log power spectrum of series of periods during self-paced forearm oscillations (Delignières et al., 2008). This average spectrum presents a negative slope in the low- frequency region, indicative of 1/*f* noise, and a flattening in high frequencies typical of additive white noise.

This comparison between tapping and oscillation was motivated by the distinction established some years ago between event-based and emergent timing processes (Robertson et al., 1999; Zelaznik, Spencer, & Doffin, 2000). Event-based timing is typically exploited in tasks involving serial discrete movement, especially finger tapping. In this case, timing is supposed

to require an explicit representation of time. Emergent timing, in contrast, is supposed to be exploited in tasks involving smooth and continuous cyclical movements (as for example, circle drawing, or forearm oscillations). In that case, timing seems governed by the dynamical properties of effectors, considered as self-sustained oscillators.

According to Delignières et al. (2004), the flattening of the slope of the log-log spectrum in high frequency shows that in oscillation motor variability affects directly interval durations via the movement trajectory (in contrast, in tapping it affects successive interval boundaries via discrete motor implementation delays). As such, the authors considered the high frequency slope of the log-log spectrum as a distinctive signature between event-based and emergent timing.

Delignières et al. (2008) proposed to model forearm oscillations with a hybrid self-sustained oscillator (Kay, Saltzman, Kelso, & Schöner, 1987):

$$\ddot{x} = \alpha \dot{x} - \beta \dot{x} x^2 - \gamma \dot{x}^3 - \omega^2 x + \sqrt{Q}\varepsilon_t, \quad (25)$$

where x represents position and the dot notation differentiation with respect to time. α represents linear damping, β and γ the van der Pol and Rayleigh non-linear damping terms, respectively, ω^2 represent stiffness, and ε_t a white noise term of strength Q. Delignières et al. (2008) showed that in its initial form, the series of periods produced by this hybrid model fluctuates randomly around a baseline period determined by the stiffness parameter. They suggested that the presence of 1/*f* noise in oscillations' periods could be due to cycle-to-cycle fluctuations of stiffness. Introducing 1/*f* noise in the ω^2 parameter, they showed that the oscillator produced series of period possessing dynamical signatures similar to those experimentally observed.

More recently, Torre, Balasubramaniam, and Delignières (in press) examined the effect of synchronization to a metronome on forearm oscillations. Basically, the impact of synchronization was similar to that observed in tapping: the series of periods became anti-persistent, and the series of asynchronies to the metronome presented 1/*f* fluctuations. They also observed a characteristic change in the shape of the phase portrait, with the appearance of an anchoring phenomenon (i.e., a thinning of trajectories in the phase plane, see also Assisi, Jirsa & Kelso, 2005; Byblow, Carson & Goodman, 1994; Fink, Foo, Jirsa & Kelso, 2000) in the vicinity of the occurrence of the metronome, and a specific asymmetry of the limit cycle trajectory.

The authors proposed a modified version of the parametric driving model by Jirsa, Fink, Foo, and Kelso (2000), obeying the following equation:

$$\ddot{x} = \alpha \dot{x} - \beta \dot{x} x^2 - \gamma \dot{x}^3 - \omega_i^2 x + \epsilon_1 \cos \Omega t + \epsilon_3 \dot{x} \sin \Omega t + \sqrt{Q}\varepsilon_t. \quad (26)$$

This model is an extension of the preceding hybrid model, with a nonlinear parametric coupling function. In this equation, Ω represents the frequency of the metronome and ϵ_1 and ϵ_3 the strength of the linear and parametric driving terms, respectively. Note that the stiffness parameter is now indexed, indicating cycle-to-cycle changes in stiffness. The authors showed that this model was able to adequately account for the experimentally observed pattern of correlations and for the specific changes in the limit cycle dynamic. These results suggest that in contrast to the discrete correction process involved in synchronized tapping, the synchronization of oscillations to a metronome involves a continuous form of coupling. More importantly for the present purpose, they show that the complex pattern of serial correlation obtained in self-paced and synchronized oscillations could be generated by classical dynamical models, on condition that one specific parameter in the equation was provided with fractal properties.

In opposition to the nomothetic perspective promoted by Van Orden, Kello, and collaborators, Torre and Wagenmakers (2009) proposed to designate as *mechanistic* this approach that seeks for task-specific models. This mechanistic approach suggests that it is possible to account for the presence of fractal fluctuations in series of performances by injecting 1/*f* noise in precise locations in classical models. This approach has the advantage to respect fundamental aspects of previous theories that are accounted for by these classical models.

Note that this approach does not contradict one of the main hypotheses of Kello and Van Orden's approach, supposing that 1/*f* noise represents the hallmark of complex systems. The originality of Torre and Delignières' approach is to suppose that 1/*f* sources could be localized in some sub-systems within the whole system. Each of these sub-systems is supposed to possess the properties of complexity, self-critical organization, metastability, which underlie the generation of 1/*f* fluctuations. West and Scafetta (2003), for example, developed the idea that Central Pattern Generators, conceived as complex neurons networks, could represent this kind of local fractal source, generating the fractal nature of gait.

Importantly, this localization hypothesis should not be understood as that of a precise localization of fractal sources, in a specified zone of the brain for example. The nature of fractal fluctuations, suggesting the cooperative interaction of multiple components acting over different time scales, rather supposes that these sub-systems generating 1/*f* noise represent independent complex networks distributed within the whole system. In other words, the mechanistic approach claims for a *statistical* localization of the fractal sources rather than for a *structural* localization in the brain or the body.

Delignières et al. (2008) introduced some "simple" modeling solutions for generating 1/*f* fluctuations. They proposed, for example, to account for fractal fluctuations in the timekeeper component of the WK model by a stochastic version of the activation threshold model (i.e., the 'shifting strategy model'). As well, they proposed to account for 1/*f* noise in the evolution of oscillator's stiffness over time by means of the 'hopping model' initially introduced by West and Scafetta (2003). The choice of these modeling solutions was motivated by previous works suggesting their theoretical, biological, or psychological plausibility (Ashkenazy, Hausdorff, Ivanov, & Stanley, 2002; Wagenmakers et al. 2004). However, their precise architectures are not of central interest. Alternative fractal generators could have been used and provide similar results (for an example, see Diniz et al., 2010). These modeling solutions should be essentially conceived as formal mathematical tools for injecting 1/*f* noise in precise statistical locations in the global models.

6. Conclusion

Over the past decades, scientists have been able to develop clear intuitions about the behavioral correlates of 1/*f* noise in human behavior. More healthy, stable, and coordinated behaviors seem to go with a clearer presence of 1/*f* noise. Less skilled and deficient behaviors show more random trial-to-trial fluctuations. Along with other dynamical measures, these dynamical system properties now become accepted as a sensitive metric for coordination, and as an indication for system complexity. Although the gained intuitions are based on a large number of empirical studies, there is still a considerable debate about the cognitive architecture that enables fractal dynamics to serve as a coordinative basis for behavior.

In this article, two theoretical approaches to 1/*f* noise in human behavior have been presented; interaction-dominant and domain-specific dynamics. According to the interaction-dominance approach, 1/*f* noise is the natural signature of a complex system in which the coordination

among degrees-of-freedom emerges from the dynamical interdependency of the system's constituents. A domain-specific account at the other hand, seeks for encapsulated sources of the observed fractal dynamics, and views the cognitive system as an aggregate of multiple complex systems; encapsulated sources of 1/*f* noise may interact but the revealed intrinsic system dynamics are idiosyncratic, not interdependent.

From the former point of view, intrinsic dynamics emerge from the multiplicative interactions that constitute the entire system. From the latter point of view, intrinsic dynamics emerge from localized parts of the underlying system. Because of this theoretical distinction, these accounts for 1/*f* noise in human behavior have previously been described as opposed and incompatible (Kello et al., 2007; Torre & Wagenmakers, 2009).

In this final section, the question is raised whether these approaches could represent complementary points of view regarding the 1/*f* phenomenon. The answer to this question is twofold, however. From one stance (1), it appears to be hardly plausible for system dynamics to emerge both from the irreducible interdependency of elemental system constituents and from elemental and reducible idiosyncratic sources. At the other hand (2), it is unlikely for one theory to yield all pragmatic answers to any question concerning human cognition (Dale, Dietrich, & Chemero, 2009). Therefore, it is essential to embrace multiple positions in debates about enigmatic empirical phenomena like 1/*f* noise in human behavior.

Based upon the second part of the answer, it is inconvenient that a pluralist position cannot easily be achieved based on empirical observations. Van Orden and colleagues have shown that changes in the presence of 1/*f* noise with learning occur across domains, principally in similar ways as the coordination of bodily and physiological processes. They also showed that 1/*f* is prevalent in dozens of parallel signals simultaneously, which would require an endless number of idiosyncratic sources of 1/*f* noise to account for the general nature of these findings (also see Kello et al., 2007; Wijnants et al., 2009a). Delignières and colleagues have empirically connected the presence and relative change of 1/*f* noise with well-established theories of motor control. Their research develops an elegant approach in which 1/*f* noise can be realistically inserted in statistically well-defined, local parts of cognitive models. Are these empirical results incompatible, and is it awkward to promote pluralism in these matters? It cannot be excluded before the fact that, under some circumstances, the cognitive system coordinates its internal degrees-of-freedom in more idiosyncratic ways, while in other contexts behavior may require feedback from its entire underlying system; hence, brain, body, environment, and their mutual history. However, such a postulate would definitely require further experimental and philosophical exploration.

More convenient is that an integration of both approaches is not a requisite for pluralism. In contrast, the road to pluralism is necessarily paved with metatheoretical distinctions. The Van Orden camp conceives of the localization of interdependent dynamics much like "[a] drunk looking for lost keys under the lamppost because the light is better there" (Kello et al., 2007, p. 551). The Delignières camp finds that "[unlike nomothetic accounts] mechanistic accounts offer the advantages of specific, experimentally testable and thus falsifiable models of human behavior" (Torre & Wagenmakers, 2009, p.314). The question of the 'complementarity' of the approaches boils down to axiomatic premises.

Axiomatic premises, whether they deal with the interdependence or the idiosyncrasy of the system constituents, are inevitable and essential in scientific research (Carello & Moreno, 2005). They clarify assumptions that stem from meta-theoretical intuitions, which have profound consequences on the practice of cognitive science. "They influence the phenomena we choose to study, the questions we ask about these phenomena, the experiments we perform, and the ways in which we interpret the results of these experiments" (Beer, 2000, p.

91). Whether one accepts the premise that 1/*f* originates from system complexity in the sense of emergent coordination or the premise that 1/*f* originates from an idiosyncratic source, such a priori assumptions need further elaboration (perhaps experimentally when testable predictions are derived, perhaps through post-hoc explanations) in order to avoid circular reasoning (Van Orden, Pennington, & Stone, 2001). In our opinion, 1/*f* noise is both intriguing and telling of system performance. In order to develop a further understanding of the role of 1/*f* noise in human behavior, the phenomenon must be studied pragmatically, preferably from a variety of different perspectives; hence, from a variety of starting premises.

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General Discussion

1/*f* scaling and coordinated performance: Five perspectives considered

Wijnants, M. L. (in preparation). 1/*f* scaling and coordinated performance: Five perspectives considered.

CHAPTER 7

Abstract

When human performances are repeatedly measured, the resultant time series of measurement outcomes presents fluctuations around a mean value. These fluctuations have long been considered as insignificant, and are typically attributed to random noise. Over recent decades, however, it has become increasingly clear that fluctuations in repetitive performance possess interesting properties, one of which the much debated, intriguing phenomenon of 1/*f* scaling. 1/*f* scaling in a time series indicates that the measured process is complex and extends over a wide range of timescales, suggesting that the measured process is assembled over multiple scales simultaneously. One of the most puzzling aspects of observing 1/*f* scaling is its clear presence in healthy, well-coordinated performance, and its relative absence in less coordinated performances. The present paper reviews a number of neurological, physiological, and cognitive studies that corroborate this claim, and secondly, confronts the five most prominent hypotheses about the presence of 1/*f* scaling in human performance with those findings.

1. Introduction

The presence of 1/*f* scaling in human performance is arguably one of the most puzzling phenomena in cognitive psychology (see Diniz et al., 2011; Gilden, 2001; Van Orden, Holden & Turvey, 2003; 2005, Riley & Turvey, 2002; Slifkin & Newell, 1998; Wagenmakers, Farrell, & Ratcliff, 2005). 1/*f* scaling represents the occurrence of fractal, self-similar processes that become nested across scales of measurement. That is, a rescaling of the time axis of repeatedly measured performances will leave the distributional properties of the signal unaffected. The phenomenon is widespread across the central nervous system, motor behavior, cognitive performances, and well beyond. For instance, many physical and physiological signals exhibit complex scale-invariant features characterized by 1/*f* scaling, suggesting a possibly common control mechanism. Because it is now well-known that the presence of 1/*f* scaling has profound impact on task performance, the phenomenon warrants serious attention.

One reason for the air of ‘mystique’ that sometimes surrounds discussions of 1/*f* scaling (e.g., Wagenmakers; van der Maas, & Farrell, 2011), is that the observation of 1/*f* scaling in itself runs against standard statistical intuitions. That is, successive observations of a repeated behavior are typically assumed to represent measurement values that are independently drawn from a Gaussian distribution, and thus fluctuate randomly from trial-to-trial. Over recent decades, however, it has become clear that movement variability rarely equates with random, Gaussian noise, and that temporal variability is usually structured and reveals specific details of the system dynamics (Gilden, 2001; Riley & Turvey, 2002; Slifkin & Newell, 1998; Stergiou & Decker, 2011; Torre & Balasubramaniam, 2011). In fact, structured variability appears to be the rule rather than the exception, and is often more revealing than aggregate information in terms of unpacking the nature of the system organization (Ihlen & Vereijken, 2010; Kello, Beltz, Holden, & Van Orden, 2007; Kiefer, Riley, Shockley, Villard, & Van Orden, 2009; Konvalinka et al., 2011; Wallot & Van Orden, 2011a).

1/*f* scaling in a response signal presents a very different type of variability than random noise, as it implies long-range dependence in the signal. The associated serial correlations decay very slowly as the number of intervening trials increases. 1/*f* scaling therefore indicates persistent serial correlations, in contrast with the traditional view that they are transient (see e.g., Gilden, 2001). One way of revealing the complex dynamics of 1/*f* scaling is through spectral analysis. Spectral analysis translates dependencies in the time domain (i.e., a pattern

of change in response time over trials) as simple features in the frequency domain using an operation called a Fourier transform, which decomposes the data series containing changes in response over trials into its constituent frequencies. Next, the power (the square of the amplitude) of each contributing waveform is plotted in a log-log power spectrum (also called power spectral density function). A log-log power spectrum from a random data series (also called white noise, shown in Figure 1a) is shown in Figure 1b. White noise is not long-range dependent, and is represented as a flat slope in a log-log power spectrum. $1/f$ scaling, in contrast, is expressed as an inversely proportional relation between (log) power and (log) frequency (hence, $1/f^1$ scaling, see Figure 1d).

This means that $1/f$ scaling expresses a nested sequence effect spanning over the entire time course of an experiment, and even beyond, that comprises undulating "waves" of relatively longer and then shorter response times that travel across the series. Specifically, faster (high-frequent) changes in response time are typically small, and embedded in overarching, slower (lower-frequent) changes of higher amplitude (see Figure 1c). A third class of variability is Brownian noise (see Figure 1e), which can be generated by adding (i.e., integrating) successive observations generated by a white noise process. Brownian noise is nonstationary, which means that variance increases over time. The slope of a log-log power spectrum of Brownian noise has a slope of -2 (hence, $1/f^2$ scaling, see Figure 1f).

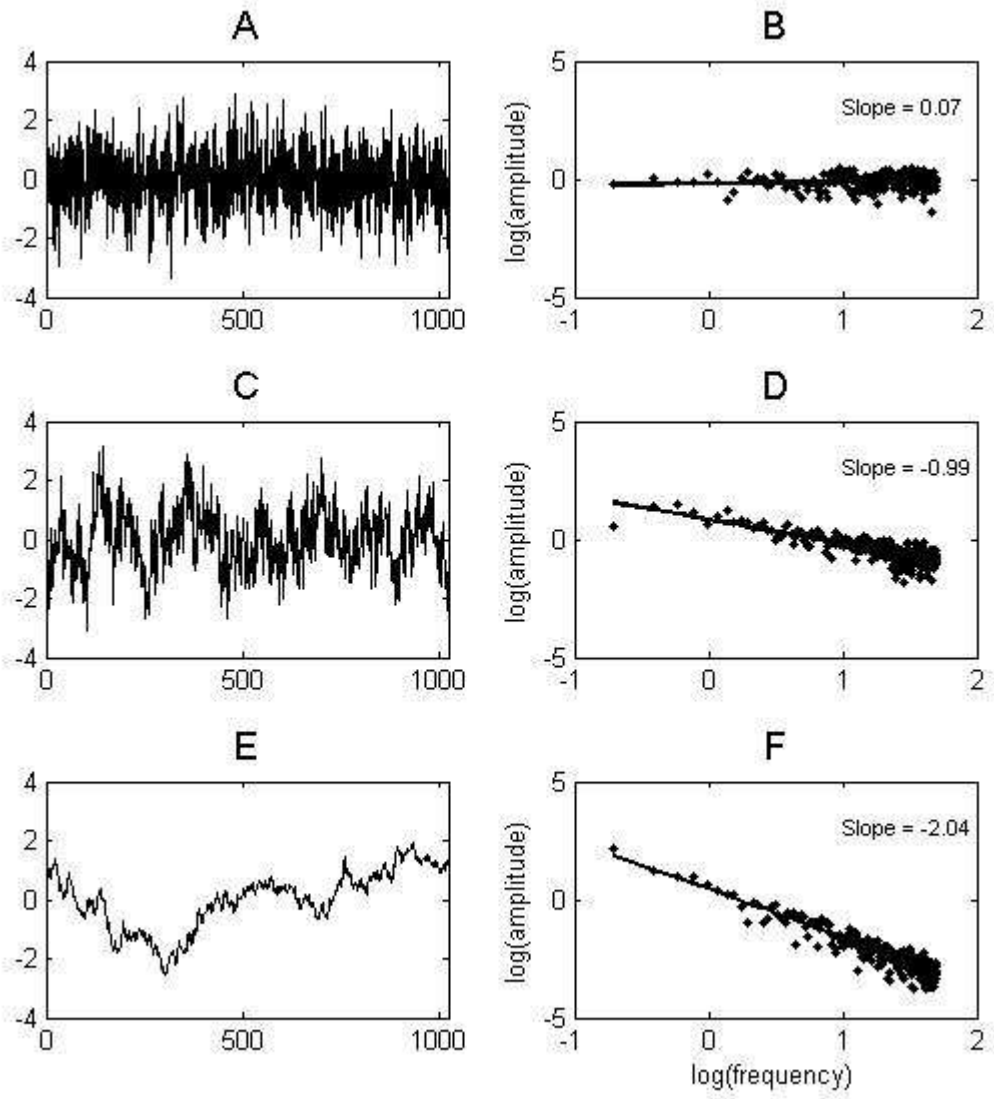

Figure 1. Three different classes of temporal variability, white noise (a), 1/*f* scaling (c), and Brownian noise (e), and their respective power spectra are shown in the respective panels at the right.

The presence of 1/*f* scaling in cognitive performances remains a hotly debated topic (see for instance, Dixon, Holden, Mirman, & Stephen, 2011; Riley, Shockley, & Van Orden, 2011; Silberstein & Chemero, 2011; Wagenmakers et al., 2011) after well over a decade of research (i.e., Gilden, Thornton, & Mallon, 1995). The majority of empirical studies have revealed a gradual shift in the scaling exponent (which is the negative slope of the power spectrum) with experimental manipulations, rather than discrete transitions from one class of variability to the other. Typically, repeated human behaviors show a scaling exponent α in the range of 0 and 1, in between random noise and 1/*f* scaling. Examples of cognitive tasks include mental rotation, lexical decision, and visual search (Gilden, 2001), simple reaction time and word-naming (Van Orden et al., 2003), forearm oscillation (Delignières, Torre, & Lemoine, 2008), synchronization to a metronome (Chen, Ding, & Kelso, 1997); implicit associations (Correll, 2008), bi-daily reports of self-esteem (Delignières, Fortes, & Ninot, 2004), and movement times in a Fitts task (Valdez & Amazeen, 2008; Wijnants et al., 2009), among others. But sometimes α varies between 1 and 2 or even beyond, often in continuous processes like

postural sway (e.g., Collins & De Luca, 1993), force production (Sosnoff, Valantine, & Newell, 2009), or galvanic skin response (Wijnants, Cox, Hasselman, Bosman, & Van Orden, 2012).

The aim of this paper is to review five pertinent perspectives on the origins of 1/*f* scaling in human cognition. Each of these competing perspectives may successfully explain the presence of 1/*f* scaling, but the perspectives postulate very distinct underlying mechanisms and opposing views on the phenomenon. First, I specifically evaluate supportive evidence for the claim that the cognitive system operates at the best of its performance when fractal dynamics govern and constitute the system. Secondly, I discuss the distinct accounts that have to deal with these findings, each with their own strengths and weaknesses. I propose specifically that questions about which mechanism may potentially produce 1/*f* scaling, should be rephrased as what explanation accounts best for the so general linkage between observed fractal dynamics and well-coordinated system performance. That is, it remains to be seen which of these perspectives deals best with the empirical evidence that has accumulated in the literature on 1/*f* scaling since the seminal paper of Gilden et al. (1995).

By reviewing the functional benefits of fractal dynamics and the contemporary theoretical interpretations thereof, I hope to offer a vehicle for theoretical progress on the topic of 1/*f* scaling in cognitive performances. That is, the steadily growing body of reliable positive evidence that contradicts or grossly surprises conventional thinking raises a number of important issues that have remained unresolved. For one, the presence of 1/*f* scaling allows cognitive scientists to investigate commonalities between the dynamics of performance across many perceptual-motor and cognitive tasks that are not expected from classical componential models that posit a single or a few fixed control structures. These communalities rather suggest the existence of processes that are interdependent across many scales of analysis, over a wide range of cognitive activities.

2. Fractal dynamics and system coordination

In this second part of the paper, I present a number of recent studies that show widespread 1/*f* scaling in the human body and in human behavior. The communalities among these studies is they all found reduced 1/*f* scaling in the presence of external perturbations, high workload, or in other situations where the system was not fully functional, healthy or coordinated. In the literature on 1/*f* scaling, typically, heartbeat intervals and gait intervals are taken as classical examples (as described below). This undervalues in a way the generality of the relation between system performance and the presence of 1/*f* scaling. Rather than an incidental finding, this specific scaling relation has been observed extremely globally, ranging from coordination at the neurological, to the physiological level, to behavior in motor and cognitive tasks, as well as in complex physical systems well beyond.

Consider for instance a biological example that hints at the generality of the claimed relation between coordinated system behavior and 1/*f* scaling. The example comes from a recent study that analyzed the spontaneous vibratory motions of the membrane of red blood cells, which, like many processes in the human body, oscillates in a 1/*f* fashion. The human body continuously produces new red blood cells (approx 2.4 million a second, e.g. Sackmann, 1995), and red blood cells compose around a third of all cells in the human body (Pierigè, Serafini, Possi, & Magnani, 2008). When red blood cells stop functioning properly, in short, many things are going to go wrong in the body. Therefore red blood cells are renewed after approximately 120 days. Interestingly for the present purpose, the membrane of red blood

cells spontaneously vibrates, or 'flickers', revealing 1/*f* scaling. Costa, Ghiran, Peng, Nicholson-Weller, and Goldberger (2008) revealed not only that red blood cells are complex over multiple timescale, but secondly, that the dynamical properties change with in vivo aging: Older cells emit less clear 1/*f* scaling, compared with the newer cells that carry more oxygen.

I started this second part of the paper with this example taken from biology, because red blood cells constitute such an important and basic system component that is strongly related with the adequate functioning of the brain and the body (and therefore likely human behavior). By linking the functional benefits for systems with fractal dynamics, as in this example, I hope to offer a vehicle for theoretical progress on the topic of 1/*f* scaling in cognitive performances. In an effort to review how general the linkage is between fractal dynamics and optimal system performance, first, neurological studies are addressed, followed by physiological studies, and then the results from motor and cognitive studies are discussed. All of these studies provide supporting evidence for the general claim that 1/*f* scaling indicates well-coordinated system behavior. In the final section of this paper, the five perspectives on 1/*f* scaling in cognitive performance will be confronted with these findings.

2.1 Pervasive fractal order in the central nervous system

Perhaps, the central nervous system is the best example of a complex system, that is, brain activation can be investigated across many different embedded levels of analysis. The finest level is the molecular scale which makes up cells, neurotransmitters etc. Courser levels of brain activity include cell membranes with their synapses, microcircuits of dentritic trees, whole neurons, local cortical circuits consisting out of nearby neurons, entire cortical regions, and interactions among cortical regions and pathways connecting them. At the coarsest scale we find the central nervous system as a whole. Evidence of scale-invariant self-similarity, or 1/*f* scaling, at all of these levels would invite to inquire whether common dynamical constraints may apply to each of these embedded scales of brain organization. Answers to such questions undoubtedly would lead to appreciably new insight into the complex organization of the brain. We may wonder whether the different levels of brain function reveal 1/*f* scaling, and whether the presence of fractal scaling properties is in fact beneficial to their function.

Anatomically, the brain reveals fractal properties in branching dendrite patterns, which maximize functionality for a fixed dendrite cost (Bassingthwaighte, Liebovitch, & West, 1994; Kniffki, Pawlak, & Vahle-Hinz, 1994; Smith, Marks, Lange, Sheriff, & Neale, 1989). Thus, fractal scaling in morphological specializations at the cellular level has a functional role (see also Harrison et al., 2002; Milosevic, Ristanovic, Stankovic, & Gudovic, 2007; Zietsch & Elston, 2005). In another example, fractal dimensions of microglia have been found to differentiate among healthy and pathological brains (Karperien & Jelinek, 2008; Soltys, Ziaja, Pawlinski, Setkowicz, & Janeczko, 2001). Also at more global organizational levels of the brain, fractal morphology yields functional advantages (Ha et al., 2005, Zhang, 2006).

Aside the spatial fractal structures observed in brain anatomy, temporal dynamics of brain activity display complex behavior across many scales: 1/*f* power-law scaling has been observed in temporal activation patterns at all levels of neural organization, from ion channels opening and closing times to cortical networks (Werner, 2010). The question of primary interest is how the dynamics of ion channels (Liebovitch & Krekora, 2002; Liebovitch & Shehadeh, 2005; Lowen , Cash, Poo, & Teich, 1997; Takeda, Sakata, & Matsuoka, 1999, Varanda, Liebovitch, Figueiroa, & Nogueira, 2000) interact with rather than concatenate to fractal spike intervals (Bhattacharya, Edwards, Mamelak, & Schuman, 2005; Giugliano,

Darbon, Arsiero, Luescher, & Streit, 2004; Grüneis et al., 1993, West & Deering, 1994) and the functional characteristics of larger scale neural ensemblies (Buzsàki, 2006; Bressler & Kelso, 2001; Freeman, Holmes, Burke, & Vanhatalo, 2003; Spasic, Kesic, Kalauzi, & Saponjic, 2010; Tognoli & Kelso, 2009; Varela, Lachaux, Rodriguez, & Martinerie, 2001; Werner, 2007).

Clues regarding the functionality of fractal brain dynamics may come from pathological brains. Deviations from 1/*f* noise have been found, for instance, in brain dynamics of patients suffering from major-depressive disorder (Linkenkaer-Hansen et al., 2005), mania (Bahrami, Seyedsadjadi, Babadi, & Noroozian, 2005), autism (Lai et al., 2010), epilepsy (Ramon, Holmes, Freeman, McElroy, & Rezyanian, 2008), and Alzheimer's disease (Abásolo, Hornero, Gómez, García, & López, 2008). These results suggest that 1/*f* noise is a natural signature of the functional coordination across the many scales of a healthy brain. If so, one would indeed expect that the presence of 1/*f* scaling in brain activation correlates with the severity of depression symptoms (Linkenkaer-Hansen et al., 2005) or the success rate of recovery from traumatic brain injury (Burr, Kirkness, & Mitchell, 2008).

The scale complexity inherent to the study of brain activity makes it an enormous challenge for neuroscience to arrive at a universal theory of brain function. One first complication comes from the fact that investigating brain activity requires different methods at each level or scale. Each of the methods available to neuroscientists yields a compromise between spatial and temporal resolution and, consequently, yields a priori choices in the organizational level of interest. No current method in isolation is likely capable of revealing the full-blown complexity of the brain, from the decimeter to the micrometer scale and from milliseconds to minutes and even longer (i.e., developmental) timescales. The pervasive presence of self-similar scale-invariant brain morphology and activity, and its relation to well-coordinated brain function suggests that if one universal theory of brain function would eventually emerge, it would likely need to take the functional role of 1/*f* noise into account.

2.2 Pervasive fractal order in the body

Many practical applications of fractal analyses in cognitive research have been motivated by initial successes relating 1/*f* scaling to the working of the body. In physiology, much effort has been exerted to reveal what 1/*f* scaling means for the coordination and flexible adaptivity and stability of the involved regulatory processes, and how the scaling structure changes with pathological conditions. The general conclusion is that deviations from 1/*f* scaling are related with the degradation and decoupling of integrated physiological systems, leading to severe disease and increased mortality risk.

For instance, heartbeat interval series show 1/*f* scaling and the clearest examples come from young and healthy adults. Deviations from 1/*f* scaling, either associated with excessive order (pathologic periodicity), or uncorrelated white noise, indicate pathological conditions like congestive heart failure and ventricular arrhythmia (Goldberger, 1997; Peng et al., 1995), and thus predict mortality (Mäkikallio et al., 2001). Smaller deviations from 1/*f* scaling have been observed in heartbeat intervals with aging (Goldberger, Peng, & Lipsitz, 2002), in obese children (Vanderlei, Pastre, Júnior, & de Godoy, 2010) and adults with Down Syndrome (Mendonca, Pereira, & Fernhall, 2011).

Also breathing rhythm reveals 1/*f* scaling behavior, and respiration intervals show deviations from 1/*f* scaling towards white noise with aging (Peng et al., 2002; West, 2006). The contrary was observed with development. Fetal breathing movements show more pronounced

examples of 1/*f* scaling with gestational age (Govindan, Wilson, Murphy, Russel, & Lowery, 2007). These findings have led to the conclusion that fractal dynamics increase the overall efficiency of the respiratory system (West, 2010). This postulate is supported by deviations from 1/*f* scaling found in asthma patients, and the observation that asthma patients with more pronounced 1/*f* signatures in breathing rhythm showed better recovery after treatment (Frey et al., 2005).

Also other physiological processes are characterized by 1/*f* fluctuation. For instance, fluctuations in blood pressure are found to scale as 1/*f* (Mutch et al., 2000, Brogan et al., 2007). Diabetic patients, however, show reduced 1/*f* scaling specifically in glucose fluctuations in the blood flow compared with healthy controls (Ogata et al., 2007; Yamamoto et al., 2010). Other examples are provided by fluctuations in colonic pressure. Yan, Yan, Zhang & Wang (2008) observed 1/*f* fluctuations in the colonic activity of the healthy subjects, while patients hospitalized for slow transit constipation showed colon pressure fluctuations deviating from 1/*f* noise towards Brownian noise; a condition yielding hardly bearable levels of pain sensation.

In physiology and medicine it is being increasingly acknowledged that a disease not only changes an average measure, such as heart rate or breathing rate, but is manifest in departures from fractal variability. Deviations from 1/*f* scaling are taken to imply a loss of physiologic control, and are often visible at very early stages of pathological development. The change in fractal dynamics with age and with disease suggested the new definition of disease as a loss of complexity, rather than the loss of regularity (e.g., Goldberger et al, 2002). With these many systems, and their self-regulatory control, estimating 1/*f* scaling reveals a huge potential to understand and improve health and system coordination (West, 2010).

2.3 Pervasive fractal order in motor control

As in neuroscience, medicine, and physiology, there has been an increasing interest in fractal dynamics in human movement science. For instance, time series of postural sway differ reliably from random noise, revealing fractal properties (e.g., Duarte & Sternad, 2008; Duarte & Zatsiorsky, 2001; Collins & De Luca, 1993). Moreover, the clearest examples of 1/*f* scaling are found in young participants, while elderly participants show less clear 1/*f* scaling in their postural dynamics (Doyle, Dugan, Humphries, & Newton, 2004), a finding which has been interpreted as indicating degraded balance control (Collins & De Luca, 1995; Laughton et al., 2003; Maurer, Mergner, & Peterka, 2004; Priplata, Niemi, Harry, Lipsitz, & Collins, 2003; Priplata et al., 2006). This interpretation was further supported by Manabe et al. (2001), who demonstrated that less clear 1/*f* scaling is present in postural sway dynamics for patients suffering from Parkinson's disease and spinocerebellar ataxia, compared to a normal population. Interestingly, fractal measures were even found more reliable than traditional measures of postural sway (Doyle, Newton, & Burnett, 2005).

These findings are consistent with the observation of 1/*f* scaling in gait intervals (Hausdorff, 2007; 2009, are reviews), which are the time intervals between successive steps in locomotion. Again, the clearest examples of 1/*f* scaling are observed in young and healthy participants, whereas with aging, gait interval series become more random. Also, the relative presence of 1/*f* scaling successfully discriminates between fallers from non-fallers in an elderly population, and between Huntington's patients and control participants (Hausdorff, 2007). Moreover, the fractal dynamics of stride intervals produced by Huntington's patients correlates strongly with the severity of the illness (r = -.78, cf. Hausdorff, 2007), suggesting that deviations from 1/*f* scaling suggest impaired control of locomotion. Hausdorff (2009) describes similar findings

in Parkinson's disease patients, and observed that among patients Parkinson's disease, the 1/*f* scaling relation in gait intervals "breaks down" and the stride-to-stride fluctuation in gait becomes very similar to white noise; each stride starts a new process, unlinked and unrelated to the previous stride. After successful treatment with proper medication, however, 1/*f* scaling becomes more prominent again in Parkinson patients' gait dynamics (Auriel, Hausdorff, Herman, Simon, & Giladi, 2006).

In another motor task, Wijnants, Bosman, Hasselman, Cox, and Van Orden (2009) took a different perspective by focusing on non-pathological performance. They presented college students with a very challenging precision-aiming task, also known as a Fitts task. The instruction was to move as fast and as accurately as possible between two circular targets with an inkless stylus. Participants were presented with five training blocks of 1100 rhythmical aiming movements. To inquire the effect of motor learning on the fractal statistics, the authors used very small targets that were positioned wide apart, and instructed the participants to use their non-dominant, least-practiced hand. This manipulation succeeded since a learning effect was established: Participants reached the narrow targets much faster after five blocks of practice, while maintaining accuracy. The participants equally showed a reliable effect of practice on the presence of 1/*f* scaling in the produced movement time series. That is, the presence of 1/*f* scaling effectively increased with motor learning.

In a later study, Wijnants, Cox, Hasselman, Bosman, and Van Orden (2011) examined the presence of 1/*f* scaling in spatial (movement amplitude) and temporal (movement time) time series in a challenging precision-aiming task, notorious for revealing speed-accuracy trade-off (cf. Fitts, 1954). Because of the difficulty of the task, participants were required to either emphasize the speed or the accuracy side of the trade-off (while equally being instructed to move as fast and as accurately as possible between targets) simply because the dual task constraints were so incompatible. The authors found that the emphasized task requirement (temporal or spatial) directly affected the presence of 1/*f* scaling. Faster participants produced clearer 1/*f* scaling in movement times, but more random dynamics in movement amplitudes, as they performed the task less accurately. Conversely, more accurate participants produced more random dynamics in movement time sequences, as they performed the task more slowly, and clearer 1/*f* scaling in movement amplitude series. This effectively led to a trade-off between spatial and temporal streams of 1/*f* scaling, contingent on the so well-established speed-accuracy trade-off.

In the same study, Wijnants et al. (2011) established strong correlations between the fractal dynamics of movement time vs. movement amplitude and the biomechanical constraint of minimizing the dissipation of mechanical energy. Faster participants, who produced clearer 1/*f* scaling in their movement time series also better capitalized on the elastic properties of the muscular system to recycle the kinetic energy of the approaching hand, arm, and shoulder in potential form, which is energetically to the benefit of the next movement. Together, this amounted to a strong coupling among measurement scales in human performance: The biomechanical details emerged within the timeframe of a single movement, while speed and accuracy are determined by entire movements. The third timescale included the fractal dynamics that extend at least up to minutes of performance, and reveal nested multi-scale properties in the dynamics of repeated movements.

Another consistent finding on 1/*f* scaling in the motor control literature is its absence in the presence of feedback, or external 'drive'. For instance, Chen et al. (1997) observed that 1/*f* scaling was absent when the task was to tap to a metronome (1/*f* scaling was observed in the

asynchronies to the metronome, nonetheless), while 1/*f* scaling was clearly present in self-paced inter-tap intervals (cf. Gilden et al., 1995). Similarly, Hausdorff (2007) describes that the external drive of a metronome breaks the long-time correlations of the natural pace and generates random variability in consecutive gait-cycles. And also in a bimanual force production task, Wing, Daffertshofer, and Pressing (2004) observed random or close to random variability when feedback was presented to the participants, while much clearer 1/*f* scaling was observed when no feedback was provided. Kello et al. (2007) and Van Orden et al. (2003) interpreted these findings as evidence for the claim that 1/*f* scaling represents the intrinsic dynamics of the cognitive system. The feedback provided, either by the experimenters or the metronome, constitutes a type of external perturbations that de-correlates the intrinsic fluctuations of 1/*f* scaling. Similarly, adding a cognitive task to a motor task in a dual-tasking paradigm, leads to reduced 1/*f* scaling in the primary motor task (Kiefer, Riley, Shockley, Villard, & Van Orden, 2009). This finding was replicated as discussed by Hausdorff (2009); when Parkinson's patients were invited to walk, while performing a challenging secondary task, their gait dynamics revealed an even more reduced presence of 1/*f* scaling.

2.4 Pervasive fractal order in human cognition

Given the previously discussed results from neuroscience, physiology, and movement science, it may perhaps not be so surprising that similar findings apply to cognitive performances. Consider Figure 2, which depicts the average 1/*f* scaling exponents observed in four different experiments; word naming (Van Orden et al., 2003), choice reaction (Kello et al., 2007), simple reaction (Van Orden et al., 2003), and precision aiming (Wijnants et al., 2009). It is clear that the presence of 1/*f* scaling gradually increases over these tasks. Note that in precision aiming and simple reaction tasks, each experimental trial is identical. Each trial yields the same stimuli and the same response. This means that external sources of variation are minimized in these task performances. Consequently, the observed variation must largely reflect internal sources, which can be seen as a clearer presence of 1/*f* scaling in those tasks.

One can readily notice the difference between precision aiming and simple reaction times themselves. Precision aiming is a cyclic task, while simple reaction times become perturbed by a discrete signal to respond at each trial, and requires a discrete response at each trial. It can be seen that the extent of this perturbation effectively leads to a reduced presence of 1/*f* scaling. The other end of the scale shows the 1/*f* scaling exponents from a word-naming task and a choice reaction task. In these tasks, each experimental trial differs, but to a different extent. That is, in the choice reaction task in question, four different signals to respond were presented, each requiring a different response. In contrast to the simple response task, this procedure introduces more external sources of variation, which is revealed by a more whitened 1/*f* signal. The task that reveals the least clear example of 1/*f* scaling is the word-naming task, in which each and every experimental trial introduces a unique signal to respond. Therefore, external sources of variation are maximized in this procedure, and the measured values reflect the intrinsic sources of variation to a lesser extent.

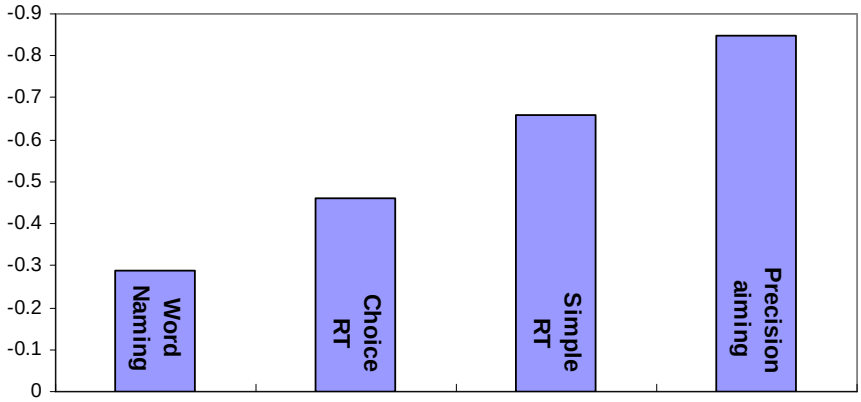

Figure 2. The spectral slopes estimated in four independent experiments are shown (i.e., 0 = white noise, -1 = 1/*f* scaling). It is shown that 1/*f* scaling become more clearly present as the number of different response options decreases (see text). The shown tasks include word-naming, choice reaction, simple reaction, and precision aiming.

A closer look at one of the tasks, choice reaction, reveals a similarly interesting finding. Ward (2002) discusses an experiment that was set up to manipulate the number of stimulus and response alternatives. In that study, Ward and Richard (2001) presented participants with a choice reaction task that consisted out of either one (simple reaction), two, or four stimulus-response alternatives. The authors effectively showed that the presence of 1/*f* scaling reduces as the number of stimulus-response alternatives increases. The scaling exponents were .60 for the simple reaction task, .37 for the two- choice reaction task, and .24 for the four-choice reaction task[1]. Similarly, the presence of 1/*f* scaling is typically reduced under high workload conditions (Clayton & Frey, 1997; Correll, 2008; 2011).

Another example of how systematic perturbations to task performance attenuate the presence of fractal dynamics comes from a recent study by Kuznetsov and Wallot (2011), who presented participants with a temporal estimation task that yielded five different conditions of accuracy feedback. In one condition, feedback was provided at every estimate, and in another condition no feedback was given at all. In the remaining conditions, feedback was displayed only if the temporal estimate deviated from the target interval by more than 50, 100, or 200 ms respectively. The results revealed an increasing presence of 1/*f* scaling in conditions where less feedback (i.e., intermittent sources of perturbation) was provided, and hence, where the intrinsic cognitive fluctuations were revealed most clearly.

A further insight into the coordinative basis of 1/*f* scaling in cognitive performances comes from a study by Gilden and Hancock (2007) who compared the performance of adults who reported ADHD symptoms with a control group of adults who did not, in a mental rotation task. The instruction was to press a key if the stimulus (a letter rotated by 0, 60, 120, 180, 240, or 300 degrees) was mirror-inverted, and another key if the stimulus was not. The authors observed very distinctive dynamical patterns of response in the reaction times of both groups. While the control group revealed fractal scaling exponents close to 1/*f* scaling, the group that

[1] Note that the scaling exponents in this four-response choice reaction task are somewhat reduced, compared with the findings of Kello et al., 2007. Note however, that these differences might be due to the fact that Ward & Richard fitted the spectral slope over all estimated frequencies, while Kello et al. (2007) only incorporated the lowest 25% of frequencies in their linear fit, as suggested by Eke, Hermàn, Kocsis, & Kozak (2002) and Holden (2005). All results in Figure 2 were obtained by fitting the spectral slope over the lowest 25% of frequencies only.

reported ADHD symptoms revealed random walk dynamics with a scaling exponent very close to 2. Thus in this study again, the more efficient system responses (i.e., the least variable responses) yielded a relatively clear 1/*f* signal, while the less coordinated, attention-deficit responses deviated from that pattern.

Another recent study (Wijnants, Hasselman, Cox, Bosman, & Van Orden, 2011) compared the response latencies of young children diagnosed with developmental dyslexia with the response latencies of non-dyslexic children in a word-naming experiment. The authors revealed that 1/*f* scaling measures reliably differentiated between both groups of readers. The dyslexic readers revealed more random response times, while average readers revealed clearer 1/*f* scaling. Furthermore, in the dyslexic group the 1/*f* scaling exponents of the response time series strongly correlated with the severity of the reading impairment, as determined by average response time (r = -0.54, the negative correlation indicates that slower responses were associated with less clear 1/*f* scaling) and standardized reading scores (r = 0.77, the positive correlation indicates that lower reading scores are associated with less clear 1/*f* scaling).

3. Five perspectives on 1/f scaling in human performance

The aim of the previous part of this paper was to show that the presence of 1/*f* scaling changes in systematic ways in experimental manipulations of physiological and cognitive phenomena. It was shown that 1/*f* scaling is observed in its clearest form in more coordinated system behavior, and deviates from 1/*f* scaling in less coordinated, less well-adapted, or perturbed system behavior. These domain-general findings suggest that temporal fluctuations in the cognitive and physiological system happen at different nested rates or scales simultaneously, which can be seen as 1/*f* scaling. This indicates that for adaptive and flexible performance to be possible, no single timescale can dominate coordination. Instead the cognitive system appears to maintain a well-defined balance between competitive and cooperative processes in a flexible coupling across the body. In this final part of the paper, I will confront five prominent, yet often competing perspectives with the empirical insights presented in the previous section.

3.1 Multi-scaled randomness

Perhaps one of the simplest accounts for 1/*f* scaling in human cognition is that 1/*f* behavior is only a reflection of the fact that a time series of repeated behaviors is affected by many independent processes that each act on their own time scale (e.g., Granger, 1980; Hausdorff & Peng, 1996; Pressing, 1999; Wagenmakers, Farrell, & Ratcliff, 2004; Ward, 2002; Wing et al., 2004). For example, consider a time series where each measured response X constitutes the sum of three different processes Y_1, Y_2, and Y_3, each evolving at their own *independent* timescale, in the form $X(t) = Y_1(t) + Y_2(t) + Y_3(t)$. If one then assumes that Y_1 is a quickly changing process, Y_2 is an intermediate process, and Y_3 is a slowly changing process, the composite, additive series of all Y's may yield 1/*f* scaling under some circumstances (see for instance, Hausdorff & Peng, 1996; Wagenmakers et al., 2004). The independent processes that evolve at distinct timescales may themselves be as general as corresponding to conscious, preconscious, and unconscious processes (Ward, 2002), neural, behavioral and cognitive events (Pressing, 1999), planning and control (Valdez & Amazeen, 2008), or automatic, conscious, and sustained attention (Wagenmakers et al., 2004).

Figure 3 shows schematically a power spectrum from repeated responses that combine the activity of a multitude of independent processes, each at their own timescale. In this

schematic representation, indeed, the specific distributions of time scales lead to 1/*f* behavior (see e.g. Beran, 1994, for a more detailed description). This suggests that the complex fluctuations and 1/*f* scaling observed in many biological systems does not convey anything "special" about the mechanism generating these dynamics. From this perspective, 1/*f* scaling is a rather coincidental event that reflects nothing more than an artifact of information processing.

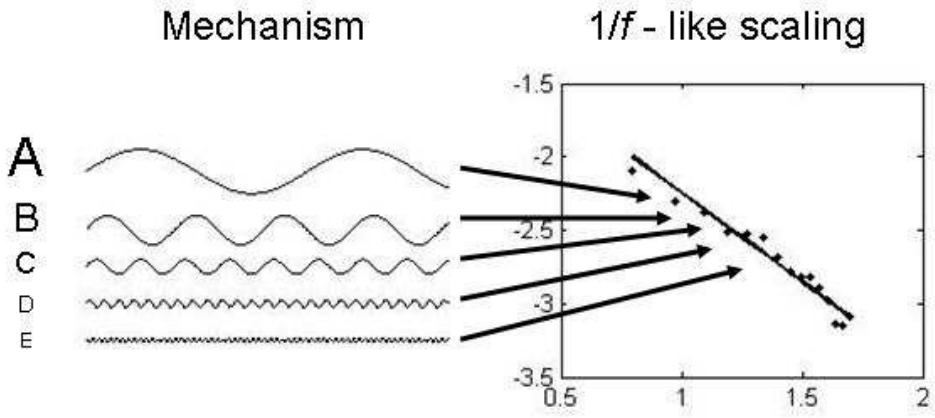

Figure 3. A schematic representation of the multi-scaled randomness construct. The left panel shows five hypothesized processes, each evolving at their own timescale. A time series composed of the sum of these processes may reveal 1/*f*-like noise in a power spectrum, which is shown in the right panel. Note that the processes are depicted schematically, and may compose random processes with differing relaxation times, rather than deterministic sine waves.

The main benefit of explaining 1/*f* scaling by aggregation of component processes is that such an explanation is conceptually simple and seemingly transparent, and may therefore 'demystify' the widespread occurrence of 1/*f* scaling (cf. Wagenmakers et al., 2004). That is, a componential model, consisting of a number of independent components, is effectively able to produce transient short-range correlations that, together, closely mimic the 1/*f* scaling behavior that is so ubiquitously observed across neurology, physiology, motor behavior, and cognition (e.g., Hausdorff & Peng, 1996; Pressing, 1999; Wagenmakers et al., 2004; 2005). Consider for instance the often cited dice-throwing algorithm in Gardner (1978). When from three dice, the first is thrown only rarely, the second intermittently, and the third at every observation, the sum of their values, when taken over a range of observations, will fluctuate in a 1/*f*-like fashion.

Nonetheless, there are a number of drawbacks associated with this account. For one, independent multi-scaled processes must exactly match the power and frequency associated with each involved component in order to coincide with a 1/*f* scaling pattern, or specific alternations thereof. However, if all parameters of the model are free, then it is very unlikely that a system would by chance choose the ``proper" parameters necessary to consistently generate 1/*f*-like noise across so many examples in neuroscience, physiology, and cognitive psychology. That is, "simulations demonstrate that if model parameters are unconstrained, the likelihood of generating 1/*f* noise is quite small. Thus, while the model can be used to generate 1/*f* noise with various scaling exponents, it is unlikely that the 1/*f* behavior observed

in many biological systems is due only to the fact that these systems are regulated by many different inputs acting on different time scales." (Hausdorff & Peng, 1996, p. 2154).

A second important drawback from multi-scaled randomness is the lack of parsimony in the model. For every independent 1/*f* signal observed in the brain, the body, and cognition, new components need to be asserted post-hoc to account for the large number of strictly additive, independent components required (Kello et al., 2007; Kello, Anderson, Holden, & Van Orden, 2008; Van Orden et al., 2003; 2005). If not, that would mean the components are shared between processes, meaning each component is no longer strictly independent, because components of perception and action would hinge on polygamies of physiological and cognitive components. In addition, consider measuring a generic 1/*f* process for ten minutes, or collecting the same process over twenty minutes, regardless whether it concerns EEG-series, stride-intervals, heartbeats, response times, or any other repeatedly measured variable. For longer time series, multi-scaled randomness implies scaling relations to bend off at the lowest frequencies (e.g. Pressing & Jolley-Rogers, 1997), because otherwise more and more short-range processes, over longer time ranges need to be invoked to keep the spectrum from flattening at the low frequencies of a power spectrum (e.g. Torre & Wagenmakers, 2009; see Van Orden et al., 2005), which is not very parsimonious either. Surely, the scaling relation may break down at extreme sides of the spectrum, but the criterion held in physics, which is observing 1/*f* scaling over at least two decades of frequencies, is generally well met in cognitive performances.

Thirdly, notwithstanding that the idea of identifying processes at different time scales is interesting and seems viable, the theoretical interpretation of the different time scales, and the identification of their source still remains quite speculative. That is, the theoretical underpinnings for how and why exactly the hypothesized processes fluctuate in that specific manner are often underspecified in multi-scaled randomness approaches. The critical question is not whether multiple independent processes could cause 1/*f* scaling in a measured signal (cf. Wagenmakers et al., 2004; 2005), but rather the specific manner in which those processes must fluctuate to corroborate the findings discussed earlier. In particular, for any observed 1/*f* time series, which are many, one needs to examine the number of reasonable time scales involved in the specific process, the approximate values for those time scales, and the relative magnitudes of each influence. Despite the simplicity of the model itself, this examination of the data is often limited to post-hoc accounts for how neural, behavioral and cognitive events, attentional processes, or consciousness components are supposed to overlap (see Torre & Wagenmakers, 2009; Van Orden et al., 2005).

When confronted with the experimental results reviewed in the previous sections, revealing consistent changes in scaling exponent in different performances, the 'demystifying' multi-scaled randomness approach of 1/*f* in human cognition, in fact, becomes an extraordinary hypothesis in itself. That is, the assumption that the observed behavior is jointly determined by many independent groups of neurons, each with their own different relaxation rate (determined by an autoregressive decay parameter) carries a massive theoretical load. The challenge is to seek for deficient system components in depression symptoms, retiring red blood cells, as well as in severe constipation, asthma, dyslexia or heart failure, among many other examples which all happen to line up as a reduced 1/*f* signature.

3.2 Regime switching

A second, related perspective on 1/*f* scaling in human cognition assumes that response processes show discrete transitions from one mode of operation (i.e., a specific mean or variance) to the next. These so-called regime switching models propose that shifts in the mean or the variance of the observed process express shifts in strategy, fatigue or attention. First, it is assumed that, over the course of an experiment, participants repeatedly change strategies. These shifts are employed for only a limited period of time. During the time that the strategies are employed, they are associated with particular threshold levels that determine the criterion amount of accumulation of information required for a response. These changing threshold criteria present themselves as different plateau-like variations (see top panel in Figure 4). Second, the speed with which the accumulation process approaches the current threshold is assumed to vary between successive measurements as a first- (or sometimes higher) order autoregressive process (see middle panel in Figure 4).

Under well-specified parameterizations regime-switching models are able to effectively generate 1/*f*-like fluctuations (e.g., Wagenmakers et al., 2004; 2005), as shown in the lower panel of Figure 4. Regime-switching models may account for non-stationarity (i.e., large criterium switches) and sudden switches in performance mode. Cognitive experiments designed to measure the degree of 1/*f* scaling are generally lengthy, as they usually require 2^9, 2^{10}, or more trials. In those experimental set-ups measured values are sometimes indeed susceptible to undesired effects of learning, fatigue, shifts in strategy and attention, and the like. This means that it is well possible that many short-range dependencies happen to line up as 1/*f* scaling, showing "that 1/*f* noise is by no means ubiquitous in psychology" (Farrell, Wagenmakers, & Ratcliff, 2006, p. 740). For instance, apparent 1/*f* scaling may simply be caused by fluctuations in fatigue, attention or strategy. Like the multi-scaled randomness approach, regime-switching models consider 1/*f* scaling as a coincidental by-product of cognition.

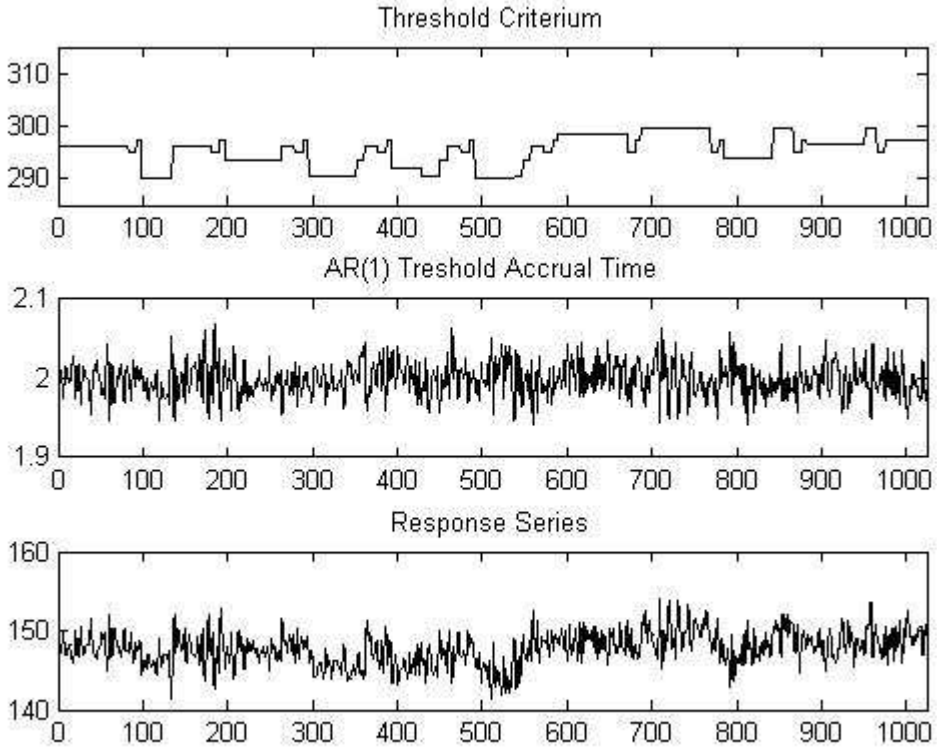

Figure 4. The top panel represents the plateaus induced by the discrete regime switches. The middle panel represents the autoregressive response variability that is inserted to the model. The response

series shown in the lower panel was created by dividing the threshold criterion (top panel) by the information accrual time (middle panel), cf. Wagenmakers et al. (2004).

It is admittedly mysterious then, that 1/*f* scaling is so genuinely observed across neurology, physiology, motor behavior and cognition. Adding the coincidences associated with each of the previously discussed empirical observations from response times to the beating of a heart and well beyond, again underscores that the critical question is not whether strategy, attention, or fatigue fluctuations may cause 1/*f* scaling, but rather the specific manner in which the component activities must fluctuate to cause exactly 1/*f* scaling, and its variations in the face of experimental manipulations. Thus, as for multi-scaled randomness, the coincidence of the discussed empirical findings renders regime-switching models as poor theoretically viable candidates to account for 1/*f* scaling in human cognition, lacking any physical motivation.

Furthermore, consider the fact that the broad family of autoregressive moving-average models can reproduce *exactly* any spectral function after the fact, as long as the spectrum has an asymptotic white region at low frequencies, because the model family has so many free parameters. A first inconvenience is that in psychological data the low frequency region does not bend off, suggesting genuine long-range dependence. Secondly, the apparent success of the model is determined by goodness-of-fit per se, and again, realistic data can only be described by a narrow set of possible parameter variation (see Gilden, 2009; Thornton & Gilden, 2005). The question is thus whether a model is a true representation of psychological processes or whether the model itself is so flexible that it is simply able to bend with the measurement error in producing good scores on goodness-of-fit. As Gilden (2009) notes: "Regardless of how small the minimum chi-square is for a particular set of parameter values, one will eventually have to reckon with the fact that the model did not predict that specific outcome; it predicted a range of outcomes, one of which may have happened to look like the data."

Wagenmakers and colleagues claim that their componential models are "specified in enough detail to allow a wide range of data to be successfully described and, more important for scientific rigor, predicted" (Wagenmakers et al., 2005, p. 114). The first part of the sentence is obviously true, but has little to do with the second part. As aptly summarized by Gilden (2009), Wagenmakers et al.'s approach can describe so much, it must in turn explain very little, because it only offers a vehicle for mathematical formalism aimed at post-hoc data fitting, lacking a supporting theoretical literature. And for this reason it is unclear what exactly the predictions are, mentioned in the second part of the sentence. How do the model parameters corroborate so many consistent changes in the presence of 1/*f* scaling across experimental manipulations? Why is 1/*f* scaling so allied with coordination in complex systems? The answers to these questions offered by regime-switching models are un(der)determined, which also makes the regime-switching model a rather speculative hypothesis if one considers the requisite list of post-hoc explanations that is currently required to dismiss 1/*f* scaling as being functional for cognition.

3.3 1/f noise + random noise

A third prominent theory about 1/*f* scaling in human performance is the two-source model presented by David Gilden and colleagues (Gilden 1997; 2001; 2009; Gilden et al., 1995; Thornton & Gilden, 2005). Their position is motivated by the fact that a power spectrum often does not exactly follow a straight line, and may reveal a flattened (hence, whitened) slope at the highest frequencies. The high and low-frequency range can thus be modeled in terms of a constrained mixture of two distinct families of variability; white noise and 1/*f* scaling. These

blended sources of variability are referred to as *fBmW*, where *fBm* stand for fractional Brownian motion and *W* for whitened, to emphasize the hybrid structure of whitened 1/*f* noises. A *fBmW* response series has following form: $RT_n = (1/f^{\alpha})_n + \beta\ N(0,1)$, where RT_n is the n^{th} data point of a signal, where $1/f^{\alpha}$ is a 1/*f* signal with zero mean and unit variance, and N(0,1) a random sample from the normal distribution with zero mean and unit variance. β denotes a free parameter that determines the relative contributions of the white noise component. Accordingly, the power spectrum is built from the correlated and uncorrelated parts in a *fBmW* signal (see Figure 5).

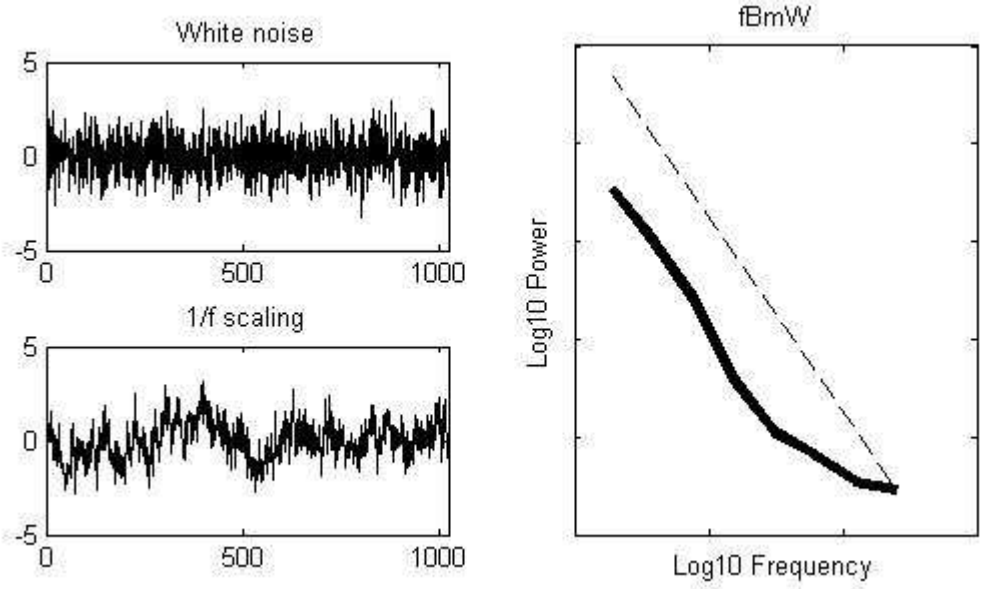

Figure 5. The top left panel shows a white noise signal, which was added to the 1/*f* scaling in the lower left panel to construct the power spectrum in the right panel, which reveals *fBmW* noise, as indicated by the flattened slope at the highest frequencies, shown as a solid line. The dashed line represents the ideal 1/*f* scaling slope.

An important difference between Gilden et al.'s account and the two models previously described is that 1/*f* scaling is conceived of as residing from a functional part internal to the cognitive system, and hence, means more than 'just' a statistical artifact. In the approach of Gilden and colleagues, the presence of 1/*f* scaling represents a genuine fractal process, indicating that cognitive processes are complex across multiple temporal scales. From this position, 1/*f* scaling is an important aspect of cognitive performance, and intrinsic to the system. A natural prediction is that 1/*f* scaling is generic to the behavior of cognitive systems, which means that it is expected a priori to observe ubiquitous 1/*f* scaling in cognitive performances.

But note that 1/*f* scaling is not exactly seen as a dynamical signature of the entire system either. 1/*f* scaling is rather hypothesized to reflect the self-organization of a component within the system, a component that is associated with elementary aspects of cognition, including the goals, intentions, and representations of a participant. Specifically, Gilden (2001) postulated that intrinsic fluctuations of a memory module, which serves the purpose of continuity of mental set (i.e., the consistency of representations, expectations and goals in the mind of the observer), are potentially causal in the formation of 1/*f* scaling. Other processes, i.e. motor processes, constitute a source of white noise, and human performances constitute an additive blend of a higher-order 1/*f* process and a lower-order white noise signal, in varying degrees in

different performances. Nonetheless, what appears to be lacking to corroborate the broad alliance between 1/*f* scaling and coordinated performance is why one independent part of the system would operate in a fractal or a non-fractal regime. This is especially puzzling because the movement system itself has been conceptualized as a complex interactive system (Kelso, 1995; Turvey, 2007) and also given that motor tasks generally show clear examples of 1/*f* scaling as well (see section: Pervasive fractal order in motor control).

Nonetheless, the mental set hypothesis may explain why the presence of 1/*f* scaling is reduced in cognitive performances when the task is not constant across trials. That is, when task parameters change unpredictably, mental set is interrupted and the aspect of performance that relies upon the 1/*f* component should be destroyed. An example given by Gilden (2001) is for instance task switching. This interpretation appears viable if one considers the varying degree of 1/*f* scaling in the four tasks presented in Figure 2. Thornton and Gilden (2005) even presented a more detailed account for Figure 2 based on their model, by showing that temporal estimation tasks (comparable with the precision aiming task in Figure 2 for the present purpose) not only reveals clear 1/*f* scaling, but also a very small contribution of the white noise component, while a choice reaction task shows less clear 1/*f* scaling, together with a much stronger white noise contribution, and word-naming data reveal the least clear presence of 1/*f* scaling, together with the strongest contribution of white noise. It thus appears that the model adequately describes the data, and that the error term gives complementary information.

The random error term constitutes a relatively unexplored aspect of performance, nonetheless. Consider for instance that only two of the studies presented in the previous part of the paper fitted Gilden et al.'s model. Most studies focused on the lowest frequencies in the signal only. Therefore it is impossible, at the time, to compare across studies the role of the random part in the model. It thus remains unclear what functional role the random component might play exactly in the coordination of mind and body. The previously reviewed studies together also suggest that an independent system component attributed to mental set (Gilden, 2001) or vigilance (Gilden & Hancock, 2007) might be too limited in scope to account for all shared instances between 1/*f* scaling and coordination in brain, body and behavior, while self-organizing accounts (see below) do not strictly necessitate the dilemma of exactly which processes benefit from 1/*f* scaling in repeated system responses.

3.4 Domain-specific, mechanistic modeling

A fourth approach to 1/*f* scaling originates from Delignières and colleagues, and has been applied to the dynamics of rhythmical movements. These authors have presented a series of concrete models, each specific to a well-defined domain of motor performance, that effectively mimic empirically observed scaling properties. Their approach is to insert a local source of 1/*f* scaling in statistically well-defined, local parts of traditional cognitive models, to account for the relative presence of 1/*f* scaling and specific spectral deviations thereof. As an example, Delignières et al. (2008) adapted the Wing-Kristofferson model (1973) for finger tapping, by inserting fractal properties into the cognitive timekeeper module assumed in the traditional model, using the regime-switching model previously discussed. Their model accounted for the scaling properties of self-paced tapping. Other examples include synchronized tapping (Torre & Delignières, 2008a), and forearm oscillations (Delignières et al., 2008).

These researchers point out that their purpose is to account for the workings of a particular, domain-specific component encapsulated in the system, and use 1/*f* noise as a constraint for modeling. Sources of 1/*f* scaling are taken to represent complex timekeeping processes that can be statistically localized in components within the system. Thus from this perspective, 1/*f* scaling represents a functional aspect of human performance related to cognitive timekeeping, but the different source of 1/*f* scaling in each domain-specific application has the form of a fractal generator that, together with non-fractal components (hence, everything else than the fractal generator), makes up the dynamics of repeated responses.

Mechanistic modeling has the advantage to be experimentally testable and thus falsifiable, and allows establishing links to current models of sensorimotor behavior. There is no a priori reason why long-range and short-range dependence should be mutually exclusive (cf. Van Orden et al., 2005; Wagenmakers et al., 2005), and the observed serial correlations are thus possibly the result of both, and mechanistic models provide a route to separate the long-range from the short-range components. Separating them has sometimes led to good fits to empirical data in different tasks, under the assumption that different system components are responsible for the differences in performance (e.g., Delignières & Torre, 2011). Moreover, the timekeeping hypothesis proposed by Delignières and colleagues appears to be consistent with the lack in 1/*f* scaling when participants synchronize to a metronome (i.e., an external timekeeper) evidenced in tapping and walking experiments as discussed previously.

One concern, however, is the approach of post-hoc data fitting. I do not wish to neglect in any way that good data fits are compelling. Yet, agreement between model and data is not proof that the model is correct (cf. Gilden, 2009). One possible pitfall of the mechanistic modeling perspective is that one may mistakenly believe that a good quantitative model fit equals qualitative or theoretical insight. A good fit to the data is a necessary, but not a sufficient criterion for a model's usefulness (Roberts & Pashler, 2000). A consideration of a model's usefulness involves, for instance, also a consideration of the theoretical foundations, the extent to which the model points to new research directions, and the generalizability of the model.

The current fear is that advanced data fitting will lead to an indefinite number of fractal generators throughout brain, body and cognition, possibly leading to multiple competing models capable of equally compelling fits to the data (Gilden, 2009; Hasselman, Seevinck, & Cox, 2011), which would question in itself the tenability of domain-specific theoretical explanations of 1/*f* scaling. Specifically, a full account for all the findings presented previously in this article would require domain-specific models for each of the observations that are so widely spread across scientific domains and disciplines. Although this could arguably lead to a well-fitting model for each separate phenomenon, the approach would likely lack the coherence a theoretical framework extending over brain, body and cognition would necessitate. Especially if one notes that the number of required timekeepers to account for the coordination of the entire system is massive (cf. Kello et al., 2008).

Another specific unclarity arises when injecting a regime-switching model in a traditional cognitive model, to explain complex system features (e.g., Delignières et al, 2008). At least it is a bit awkward since properties of complexity, self-critical organization, and metastability underlie the generation of 1/*f* fluctuations, while the fractal properties that are injected in a componential model, themselves only constitute coincidental statistical artifacts. For instance, Delignières and colleagues acknowledge that "A partir du moment où un système produit ce type de fluctuations, toute hypothèse simpliste, visant à réduire son fonctionnement à

quelques processus élémentaires, doit être définitivement abandonnée … Même dans les tâches les plus basiques, à l'exercice routinier, la performance émerge des interactions complexes à l'intérieur du système, entre les innombrables éléments qui le composent. Il serait vain de tenter de résumer un tel système autour de quelques principes macroscopiques linéaires. [*From the moment that a system reveals this type of [1/f] fluctuations, all simplistic hypotheses that aim at reducing the functioning of the system to a small number of elementary processes, should be abandoned … Even in the most basic, repetitive tasks, human performance embodies complex intrinsic interactions among the numerous elements that compose the system. It is inutile to describe such systems using macroscopic linear principles.*]" (Delignières & Torre, 2009, p. 50-51). Nonetheless, Torre and Delignières (2008b, p. 287) conclude that "according to the nature of the task, effectors are engaged in different timing control modes, and … coordination builds on these intrinsic componential dynamics." Although componential, mechanistic models may potentially benefit from borrowing ideas from complexity science, resolving the apparent contradiction remains largely unexplored territory.

3.5 Interaction-dominant dynamics

A fifth perspective conceives 1/*f* scaling as the natural outcome of complex, living systems. In the true physical sense, complex systems are systems that consist of a set of interrelated and interdependent parts with an almost infinite amount of degrees-of-freedom that cohere into a coordinated functional system. The parts dynamically interact in non-linear ways, a conceptual metaphor referred to as interaction dominance (e.g., Van Orden et al., 2003). That is, the intrinsic dynamics of the components matter less than the mutual interactions among components, which occur at multiple embedding time scales. This position is a departure from the more traditional view on human cognition that conceives human performance as caused by a number of distinct components, for example, regions of the brain, internal clocks or other information-processing devices, whose internal dynamics, when integrated, account for the observed performance (hence, for instance the four perspectives previously discussed). This convention can be referred to as component-dominant dynamics because the intrinsic activities of the components are held to be much more influential, much more dominant in determining the observed performance, than the interactions among the components.

The starting point of the interaction-dominance approach is that the conventional way of thinking about cognitive processes underestimates the number of temporal scales on which cognitive activity is actually assembled. The interaction-dominant perspective claims that cognition is more than a collection of independent processes operating in a modular cognitive system. Interaction-dominance entails that the same processes govern cognitive performance in very short and very long time frames. Any measured behavior nests processes at faster time scales, and in turn, is nested within processes at slower time scales, and the behavior of any one process at any one time scale is susceptible to, and reflective of, the behaviors of all processes over many time scales. That is, from this perspective 1/*f* scaling in human cognition means that the many processes involved interact so completely, up to the periphery of the nervous system, that one can no longer parse the individual activity of any component apart since each component has the ability to change the relevant parameters of the interaction between the elements constituting the system (Kloos & Van Orden, 2010; Van Orden et al., 2011). The 1/*f* scaling relation is considered as the essential outcome of this interdependence across multiple temporal scales.

GENERAL DISCUSSION

In interaction-dominant systems control is distributed rather than localized as in specialized devices that form efficient causes for behavior. Coordinated system performance is therefore taken to emerge through the interdependence and cooperation of processes that operate at many timescales simultaneously. It is further assumed that more efficient and coordinated systems yield a tighter coupling of mutually constraining timescales of performance, and consequently clearer 1/*f* scaling, through self-organization (the spontaneous organization that coordinates system behavior in the absence of a central controller) and emergence (the appearance of features that are not implicit in the parts of the system).

The interaction-dominant approach is a viable explanation for the presence, and changes in the presence, of 1/*f* scaling in the activity of brain, body, motor system, and cognition. Self-organizing systems fluctuate as 1/*f* scaling because local interactions extend over the entire system, over multiple embedded timescales. The interaction-dominant perspective parsimoniously explains (using a common style of system organization) why 1/*f* scaling is so generic to the behavior of such a wide variety of phenomena. To give rise to 1/*f* scaling, a system does not depend on the behavior of a specific sub-system, but rather coordinates its behavior system-wide. As a consequence, one can not dissect functionally entangled cognitive phenomena into component processes. Coordinated system performance thus involves a multitude of processes that evolve on a multitude of temporal scales, which can be seen as a clear fractal signal.

A further natural prediction from interaction-dominance, confirmed empirically, is that external perturbations to the system reduce or de-correlate the 1/*f* signal, regardless of the specificity of a certain task or level of analysis (e.g., Kello et al., 2007). Figure 2 shows that it is reasonable to believe that the 1/*f* fluctuations which govern the cognitive system are obscured when external variation in an experiment increases. For example, external manipulations of task demands may constitute sources of white noise. Such random perturbations to behavior caused by external factors disrupt the intrinsic dynamics, thereby obscuring their signature. Thus, unsystematic changes across trial measurements show themselves as ‘‘whitened’’ signals of 1/*f* scaling, as they reduce the presence of 1/*f* scaling in the now de-correlated behavioral signal. Conversely, when unsystematic sources of external perturbation are minimized, white noise is reduced and 1/*f* scaling is more clearly present.

Nonetheless, some authors remain reticent or cautious to embrace an interaction-dominant position in the study of cognitive phenomena. That is, if emergent, spontaneous, and self-organized coordination would explain such a wild variety of results, then the concepts relied on in the rationale are suspicious of being underspecified, and therefore arguably neither testable nor falsifiable (Torre & Wagenmakers, 2009). In other words, an often posited challenge for interaction-dominance is to reliably predict empirical observations, which suggests a surprising unawareness, nonetheless, that power-law scaling relations and their alternations with experimental conditions are theoretical predictions that can be derived a priori from interaction-dominance.

For instance, Diniz et al. (2011) provided such a list of predictive criteria. The first criterion for accepting interaction-dominance is that 1/*f* scaling is ubiquitous in human performance. Because the embodied mind is considered a fractal system in both its architecture and dynamics, it would be inconceivable to only observe deviations from random noise in a large majority of measurements of repeated behaviors. Aside from actual measurement errors or other potential artifacts, some degree of power-law scaling should be present in any example of a repeated performance, and more generally, in any physiological process of the human

body. Secondly, as described above, the relative presence of 1/*f* scaling should be obscured when sources of perturbation (i.e., external variation) are increased (hence, Figure 2). The third criterion, central in this paper, is that more coordinated behaviors should reveal a clearer 1/*f* scaling signature, and as discussed in previous sections, there is a long list of supportive empirical findings that is unlikely conclusive. Fourth, 1/*f* scaling should be accompanied by additional evidence for emergence and self-organization. Fractal scaling estimates are not the only tools available to complexity science. There exist a vast number of mathematically well-defined methods and techniques to analyze the complexity of behavioral dynamics that should support the emergence of dynamical patterns otherwise, as the scaling exponents become attracted to the $\alpha = 1$ of 1/*f* scaling. As a last criterion, an indefinite numbers of $1/f^{\alpha}$ signals should exist in any behavior, where usually $0<\alpha<2$. These are in fact utterly strong claims, considering that 1/*f* scaling is traditionally considered a functional and statistical nuisance from mainstream thinking in psychology. And as Stephen and Van Orden (2011, p. 4) put it, "we are testing theory-driven hypotheses and failing so far to reject them".

A related concern is whether the application of concepts and mathematical tools from complexity science and nonlinear dynamics to cognitive phenomena can lead to a notable advance in the understanding of cognitive activities, and specifically when such applications are not accompanied by concrete mechanistic models. That is, some scientists have argued that, in order for interaction-dominance to be testable and falsifiable, the equations that govern the system should be written out (Diniz et al., 2011; Wagenmakers et al., 2005). Van Orden et al. (2005) have spelled out some of the difficulties that may arise at this point. For one, "there is presently no workable entry level below the level of the emergent phenomena themselves … emergent macrolevel behavior is antithetical to the conventional reductive pursuit of cognitive mechanisms" (Van Orden et al., 2005, p. 121; see also Wijnants et al., in press). While it seems doable to postulate adequate models that describe the functioning of, for instance, red blood cells, motor behavior or brain activity, it remains unclear as to at which of these levels one should start in a reduction of an interaction-dominant system in the true physical sense (i.e., a system in which these components are intrinsically intertwined). Therefore, support for interaction-dominance is currently limited to empirical results (i.e., observing theory-supported changes in the presence of 1/*f* scaling following careful experimental manipulations), analogies with simplified physical models (e.g., an Ising model, see Kello & Van Orden, 2009, or a sandpile model, see Bak, Tang & Wiesenfeld, 1987), other phenomena that reveal analogous self-organizing properties (e.g., convection rolls or ecosystems; Jensen, 1998; Jørgensen, Mejer, & Nielsen, 1998, among many other examples), and critical network models (e.g., Bertschinger & Natschlager, 2004; Kwok & Smith, 2005).

4. Conclusion

In this paper I provided a discussion about the linkage between the presence of 1/*f* scaling and coordinated brain, body, motor, and cognitive activities. Specifically, it has been argued that 1/*f* fluctuations govern healthy, flexibly-stable system behavior regardless of the scale of observation, from the level of the cell up to the level of brain, body, and cognition. 1/*f* scaling has triggered a lot of controversy over recent years as an empirical phenomenon. The goal of the present paper was to advance this debate, by focusing on the broad range of empirical observations that are so explicitly available across the boundaries of scientific domains. The question posed was how to understand the close linkage between 1/*f* scaling and system coordination. While the contrasted perspectives may provide different answers to these questions, each of the discussed approaches may potentially account for the presence of 1/*f* scaling *per se*. Therefore, the specific suggestion here was to rephrase the question as to

which of the approaches accounts best for the so general linkage between observed fractal dynamics and coordination in the analyzed system.

In summary, Wagenmakers et al. have laid out a solid argument showing that the presence of 1/*f* scaling (per se) should not be taken as exclusive evidence for self-organization and complexity. Their argument indeed challenges the enterprise of observing (some extent of) 1/*f* scaling in some measure in some task and concluding that the system under scrutiny is complex, rather than computational-representational. The goal of the present paper was actually to step beyond a discussion about the presence versus non-presence of genuine 1/*f* scaling, however, and to question instead how and why it is that the relative presence of 1/*f* scaling changes so consistently across different manipulations of task, condition, and level of analysis. If one considers the unexpectedness of these observations, based on Wagenmakers et al.'s modular approach; the post-hoc explanations required are massive. And to be fair, the authors' defense has not gone any further than simply expressing the personal opinion that studies that include 1/*f* scaling are too "limited, superficial, and overly general" (Wagenmakers et al., 2011, p. 4) to be of any use for science. In my humble opinion, this simply ignores the nearly 100 peer-reviewed studies cited earlier in this paper, which does not seem specifically useful to science either. Under the current state of affairs, therefore, it seems unwarranted to categorize studies addressing the functional role of 1/*f* scaling in behavior as "mostly speculation, wrapped in jargon, inside wishful thinking" (Wagenmakers et al., 2011, p. 5).

Quite to the contrary, although undismissable questions remain to be answered and important challenges lie ahead, studying 1/*f* scaling and allied concepts in human performances arguably has the potential to answer the tougher type of question about the scales and modes involved in coordinated human activities. This has been recognized by Gilden and colleagues and Delignières and colleagues in their respective approaches, since these authors have focused specifically on observed changes in the extent of 1/*f* scaling in different performances, including changes that may emerge from nonlinearity in the power spectra. Their arguments clearly go beyond the initial concerns like 'is-there-really-1/f-noise', 'is-it-everywhere', and 'does-it-behave-like-a-pile-of-sand', raised by Wagenmakers et al.

An important difference between the approach of Gilden and colleagues, and the approach of Delignières and colleagues is that Gilden's model describes human performance exactly at the level of the emergent phenomena. If one accepts 1/f scaling as an emergent phenomenon, Gilden's modeling approach seems be more adequate compared with the domain-specific models proposed by Delignières and colleagues. If one does not accept that claim, however, Delignières and colleagues should be granted more specific and detailed micro-scale descriptions, which are more elegantly equateable with the modular tradition in cognitive science. Nonetheless, both approaches share the componential thinking that underlies the criticisms expressed by Wagenmakers et al., as they seek for fractal mechanisms in some encapsulated part of the cognitive system, a strategy that sets these approaches off against interaction-dominance.

While the perspectives presented by Wagenmakers and colleagues and Delignières and collegues are yet to account for the generality of the association between 1/*f* scaling and coordinated human activities, Gilden's model is in fact much more widely applicable and generalizable. It remains unclear nonetheless, whether the distinction between cognitive 1/*f* noise and random motor noise remains tenable given the thin line separating motor behaviors from cognitive behaviors (e.g., Clark, 1999; Smith, 2005; Varela, Thompson, & Rosch, 1991).

Also the accompanying phenomenological account (hence, breakdown of mental set or vigilance) might be to narrow to account for the *totality* of presented changes in 1/*f* scaling.

Interaction-dominance, however, does provide one general explanation for the discussed findings, using principles of self-organized control common among all of the discussed studies. From an interaction-dominant perspective, it is argued specifically that the association of 1/*f* scaling and coordination processes is too general to be captured by either task or component specific explanations. These findings rather seem to suggest a broad connection between 1/*f* scaling and the self-organization across processes of mind and body (Van Orden et al., 2011).

Answering the question of which perspective is most successful in dealing with the broad association of 1/*f* scaling and coordination admittedly boils down to what is considered to count as evidence. This in turn, depends on a priori theoretical assumptions regarding the kinds of variables and relationships that considered relevant in the first place, and some of the current debate among the perspectives stems from incommensurate assumptions. Nonetheless, regardless of the inevitable meta-theoretical assumptions that are in play in scientific inquiry, a mutual goal among the perspectives should be to pursue explanations of cognitive performance that can accommodate reliable and compelling empirical evidence. As it stands, the list of converging evidence discussed in this paper is appears to meet that standard, and the component-based approaches have failed so far to address this growing line of evidence that corroborates the theory-driven predictions of interaction-dominance.

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That said, by looking forwards rather than backwards many challenges can be stipulated that lay ahead. For one, if one considers the vastness of streams of 1/*f* scaling across brain, body and cognition, and one eventually accepts that any of these signals suggest massive interactions to underlie them, how then do these many streams relate? Surely, for instance multiple organ failure can be predicted from alternations from fractal dynamics in heartbeat (Tibby, Frndova, Durard, & Cox, 2003) or body temperature (M. Varela et al., 2006), but how far up the periphery of the nervous system and the environment do interdependent 1/*f* streams extend in constraining actual human performance? Under the current state of affairs, unfortunately, we are restricted to prudent speculation. Clearly, no one-to-one mapping has been found of scaling exponents of eye or hand movements, response times, brain activity, postural sway, and peripheral signals like galvanic skin response or fractal parameters in the environment, and alternative mappings remain largely unexplored territory. A potential future direction in this regard could be the investigation of multifractal structure, whose presence would suggest that a single scaling exponent as in 1/*f* scaling is in fact an oversimplified description of reality. Thus is, multifractals comprise a distribution of scaling exponents across scales within a measured signal. With their explanatory copyrights exclusively assigned to interaction-dominant dynamics (Ihlen & Vereijken, 2010), multifractals provide a rich soil for cultivating the ‘how and why’ of fractal cognition, that could potentially shed light on how distinct streams of 1/*f* scaling could or could not be functionally interdependent.

More generally, challenges for future research lay in the consistent couplings of phenomena across different measurement scales in attempts to conceal the principles that coordinate human behavior. While a large majority of theories and models in cognitive psychology exclusively pertain to phenomena at fixed measurement scales, theoretical and practical insight is likely to be gained exactly outside that box of conventional thinking. That is, the concept of fractals provides an exciting tool that surpasses the status of metaphor as far as human cognition is concerned (cf. Wijnants, 2006). Fractals provide an economical yet

powerful architecture for efficiently propagating information throughout a network (for a well-established example, see Daubechies, 2006), that allows for soft-assembled, context-sensitive behavior in the respective system (Van Orden et al., 2011). In addition, approaching the cognitive system as genuinely fractal is biologically plausible, an argument that is often undervalued in the debate.

That is, the massive attention for 1/*f* scaling across an extremely wide range of scientific disciplines (i.e., physics, biology, chemistry, ecology, neuroscience, astronomy, seismology, linguistics, robotics, and cognitive psychology, among other disciplines) has not come out of the blue. There exists extensive reviews of the application of fractal techniques in medicine as well, and not in the least because of their ability to actually predict mortality (e.g., Huikuri et al., 1998; Mäkikallio et al., 2001, i.e., an arguably clear example of breakdown of a coordinated complex system), whereas conventional variability measurements do not differ between survivors and nonsurvivors (e.g., Lundelin et al., 2010). Knowing that the association between 1/*f* scaling and coordinated system behavior remains upright across such a variety of empirical phenomena, raises the question why it would than be radical to expand the implied interaction-dominance with empirical observations of cognitive phenomena that are revealed by the very same system? After all, with the abundance of self-similarity and power laws in cognitive activities, in the end, any theory or model trying to describe cognitive systems is fundamentally challenged to corroborate these empirically observed power-laws that are so pivotal to coordinated human behavior.

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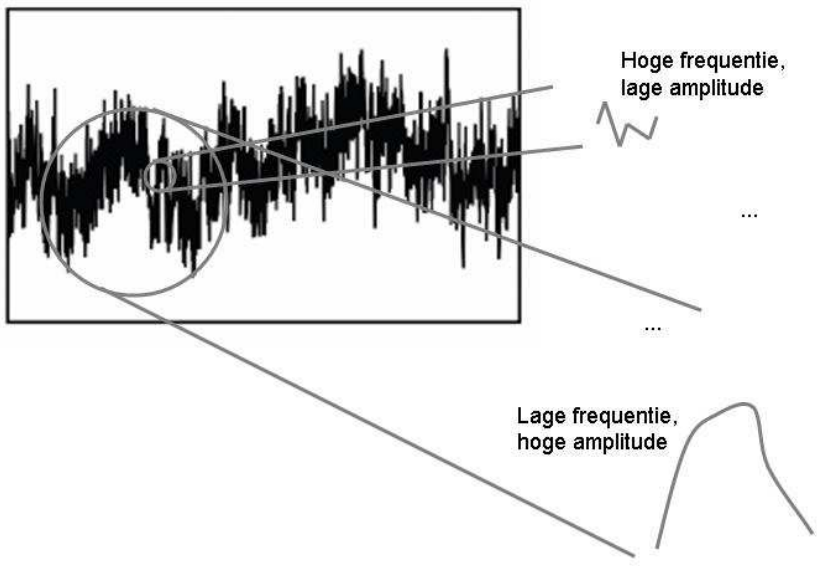
Nederlandse Samenvatting

Achtergrond

Wat hebben een Bach-concerto, een aardbeving, een zwerm vogels in vlucht, EEG, ERP, en MRI-signalen, vibraties in het membraan van rode bloedcellen, hart- en ademritme, bewegingstijden, en opleestijden van woorden met elkaar gemeen? Niet zoveel zou men op het eerste gezicht denken. Nochthans is er een opvallende gelijkenis tussen deze zo verscheiden fenomenen. Al deze processen vinden plaats in de tijd, en nog opvallender, het zijn allen processen die een een 1/*f* schaalverhouding vertonen in de dynamische structuur van hun gedrag. Het is deze ogenschijnlijk universele dynamische eigenschap dat het onderwerp vormt van dit proefschrift. Aan de hand van monofractale analyses en faseruimte-reconstructie technieken, werd onderzocht of, hoe, wanneer en waarom 1/*f* fluctuaties vorm geven aan cognitieve processen. Men kan het huidige proefschrift dan ook plaatsen in de onderzoekslijn die is onstaan sinds de publicatie van het artikel '1/*f* noise in human cognition' van David Gilden en collega's, dat in 1995 verscheen in Science Magazine, en dat een eerste aanleiding vormde voor de verhitte debatten die in het eerste decenium van de 21ste eeuw gevoerd werden in de meest aantoongevende tijdschriften binnen de experimentele psychologie.

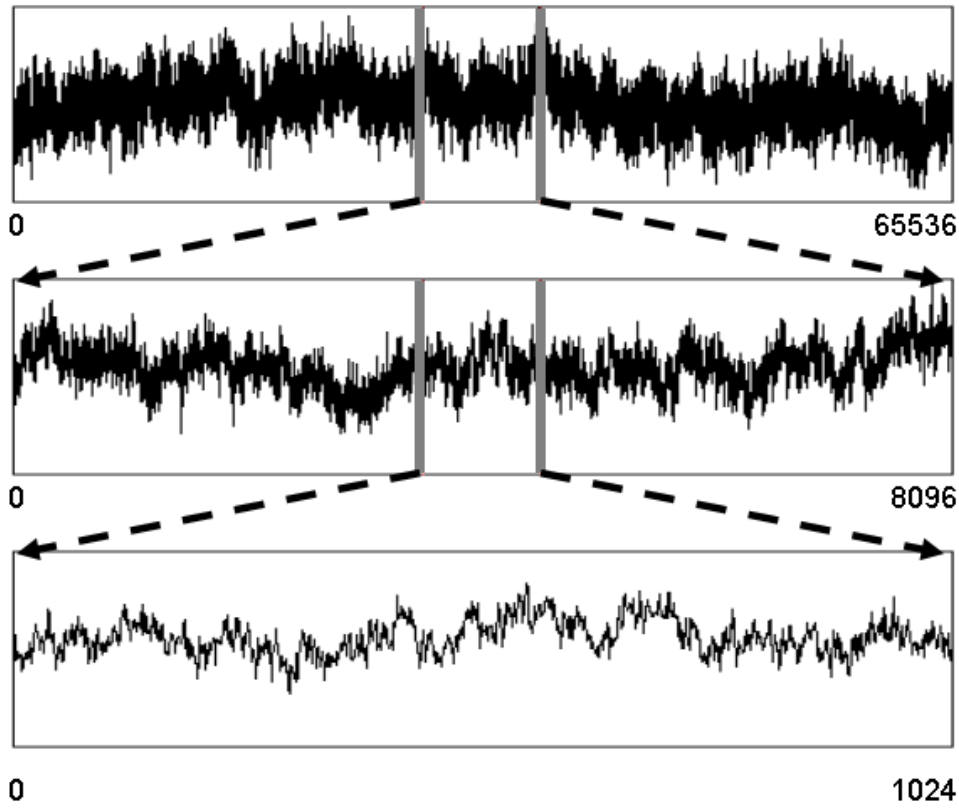
Een 1/*f* schaalverhouding impliceert dat sequentieel gemeten waarden in een tijdserie afhankelijkheden (of auto-correlaties) vertonen op verschillende tijdschalen. Een gemeten gedrag op moment A is dus niet onafhankelijk van hetzelfde gedrag op moment B of moment Z. In tegenstelling, de veranderingen in het gemeten gedrag zijn *lange-termijn afhankelijk.* Deze temporele afhankelijkheden hebben een specifieke structuur, en dit is te zien in Figuur 1. Snelle, en dus vaak voorkomende veranderingen in reacties zijn klein, en vertonen dus een lage amplitude, en tragere veranderingen vertonen een grotere amplitude.



Figuur 1. Snelle (vaak voorkomende) veranderingen in responstijd zijn klein (lage amplitude), trage (minder voorkomende) veranderingen zijn groot (hoge amplitude), ongeacht de tijdschaal van observatie. Dit resulteert in lange-termijn afhankelijkheid ('*long-range dependence*').

Deze relatie tussen frequentie en amplitude blijft onveranderd, ongeacht de schaal van observatie. Of men nu kijkt naar 20, 200, of 2000 metingen, de hoog frequente schommelingen met een lage amplitude zijn steeds genest in lager frequente schommelingen,

met een hogere amplitude, binnen het gemeten signaal. Omdat deze veranderingen zich tegelijkertijd afspelen over verscheidene tijdschalen in geneste vorm (erg lange termijn, een middelmatige termijn of een erg korte termijn, en alles er tussenin), kan gesteld worden dat het signaal geen onderliggende karakteristieke tijdschaal bezit; het signaal is '*schaal-vrij*'. Dat wil zeggen dat het herschalen van de tijdas van een tijdseries de eigenschappen van de onderliggende verdeling onveranderd laten (zie Figuur 2), een phenomeen dat in de wiskunde statistische zelf-gelijkendheid wordt genoemd.



Figuur 2. Statistische zelfgelijkendheid in een tijdseries bestaande uit herhaalde metingen.

Het observeren van een 1/*f* schaalverhouding in cognitief onderzoek staat in schril contrast met de gebruikelijke statistische aanname dat een tijdserie van herhaalde metingen uit willekeurige ruis bestaat. Dit betekent dat verondersteld wordt dat een tijdserie kan beschreven worden als een verzameling van samples, willekeurig getrokken uit een Gausiaanse, of normale verdeling. Een gevolg is dat er geen correlatie is tussen een sample genomen op één punt in de tijd, en een andere sample getrokken op een ander punt in de tijd. Met andere woorden, er wordt vanuit gegaan dat herhaalde gedragingen willekeurig geordend zijn.

Mede hierdoor is het gebruikelijk om cognitieve processen op een statische manier te onderzoeken, bijvoorbeeld op basis van gemiddelde waarden. Immers, indien men voldoende meetpunten verzamelt, komt de gemiddelde waarde dichter bij de 'ware' score omdat random ruis rondom het gemiddelde zichzelf uitmiddelt. Hiervan uitgaande kan de variabiliteit rondom de gemiddelde waarde dus volledig beschreven worden op een continuum van erg variabel tot erg stabiel. En net omdat er a priori wordt aangenomen dat er geen structuur is, en

dat men dus te maken heeft met onafhankelijke metingen, ligt de nadruk gewoonlijk dus op de *mate van variabiliteit* en niet op de *temporele structuur van die variabiliteit.*

Dit proefschrift richt zich precies op deze temporele structuur van cognitieve processen. Toegegeven, de naïve lezer die dit proefschrift aanvat met deze Nederlandse samenvatting, zal zich op dit punt mogelijks afvragen wat deze dynamische 1/*f* structuur nu precies betekent voor cognitie. Een eerste implicatie van een 1/*f* schaalverhouding is dat het betrokken proces plaatsvindt over verschillende, gekoppelde tijdschalen die niet statistisch te onderscheiden zijn. Dit suggereert dat eenzelfde proces verantwoordelijk is voor variaties in gedrag die zich evenzeer afspelen op een erg lange tijdschaal (bv. meerdere minuten of langer) als over een kortere tijdschaal (bv. milliseconden).

Het is op dit punt dat de fractale eigenschappen van het systeem (m.n., zelfgelijkendheid en schaalinvariantie) betekenisvol worden. Deze eigenschappen suggereren namelijk dat variatie in menselijk gedrag voortvloeien uit iteraties van positieve feedback, doorheen en vanuit het gehele systeem. Deze instantane, systeem-wijde informatie vormt de basis voor de emergente temporele patronen van variatie in het gecoordineerde gedrag van het dynamische systeem. Deze complexe temporele patronen van variatie geven inzicht in interafhankelijkheid van de betrokken processen, dat wil zeggen, gedrag dat voortvloeit uit de wisselwerking tussen componenten eerder dan uit de activiteit van individuele componenten op zich.

Deze opvatting vormt dan ook de antithese van de heersende *modulariteitsgedachte* binnen de cognitieve psychologie, die de theorie-constutieve basis vormt voor het statistisch en neurologisch localiseren van discrete cognitieve processen. In deze traditie heeft elke module of component een eigen functie, een idee dat de basis vormde van de cognitieve revolutie in de jaren 50 van de 20ste eeuw. Sinds de opkomst van de computer, en de daaruit voortvloeiende informatieverwerkingstheorie heerst er een vaak impliciet enthousiasme voor de computermetafoor als model voor cognitie, waarin elke component computationele operaties uitvoert op discrete symbolische representaties. De temporele aspecten van cognitieve processen die in dit proefschrift besproken worden staan haaks op deze traditie. Een 1/*f* schaalverhouding suggereert dat het onmogelijk is om de componenten onafhankelijk van elkaar te beschouwen, omdat de wisselwerking tussen componenten meer bepalend blijkt voor gedrag dan de losse activiteit van individuele componenten. Een gevolg is dat het onmogelijk is om het gedrag van een dergelijk systeem te reduceren tot een lager niveau van component-gedreven oorzaak-gevolg effecten, ook wel ‘biljartbal-causaliteit’ genoemd.

Onderzoek

Het doel van dit proefschrift was om de coordinatie van cognitieve processen te onderzoeken met bovenstaande in het achterhoofd. Namelijk, vanuit een complexe systemen benadering bestaat een efficiënt, en flexibel doch stabiel systeem uit een complexe coordinatie tussen de componenten waaruit het systeem bestaat. Deze coordinatie is afhankelijk van systeem-brede positieve feedback, wat in een tijdserie van het gedrag van het bestudeerde systeem te zien is als een 1/*f* schaalverhouding. Minder efficiënt gecoordineerde systemen kunnen hier op twee verschillende manieren van afwijken. Ten eerste kan het systeem uit een aantal onafhankelijke sub-componenten bestaan. In dat geval zal de tijdseries van herhaalde gedragingen veel meer random of willekeurig geordend zijn, en dus een minder pertinente fractale schaalverhouding vertonen. Een tweede mogelijkheid is dat het systeem slechts gedomineerd wordt door een klein aantal subcomponenten, wat resulteert in strikt geordend en voorspelbaar gedrag. Gedrag gedomineerd door een 1/*f* schaalverhouding lijkt dus een gebalanceerd evenwicht

tussen stabiliteit en flexibiliteit, onafhankelijkheid en voorspelbaarheid, of willekeurigheid en starheid van het systeem, of met andere woorden, een optimaal functionerend systeem.

Deze these gaf aanleiding tot een aantal testbare hypothesen en vormde de motivatie om de rol van 1/*f* schaalverhoudingen in cognitieve processen nader te onderzoeken. Met in het achterhoofd dat een 1/*f* schaalverhouding in sommige situaties meer en in andere situaties minder prominent aanwezig is, wordt er in het huidige proefschrift een reeks van experimentele studies besproken met het doel om de sterkte van de schaalverhouding te manipuleren. Deze studies bevestigden het initiële idee: beter gecoordineerd gedrag hangt samen met een duidelijker 1/*f* patroon.

Overzicht

Een eerste studie (**zie Hoofdstuk 2**) was gebasseerd op een zogenaamde Fitts taak. In een Fitts taak worden participanten geïnstrueerd om zo snel en zo nauwkeurig mogelijk heen en weer te bewegen tussen twee visuele doel-objecten, met een inktloze pen in dit geval. Deze studie was ontworpen met als doel om het effect van training van de arm/hand te meten. Om een motorisch leereffect te bewerkstelligen in een dergelijke ‘overleerde’ taak, werd een taakconditie gebruikt met een erg hoge moeilijkheidsindex. Er werd aan de participanten gevraagd om de niet-voorkeurshand te gebruiken bij het uitvoeren van de taak. In totaal werden vijf trainingsblokken aangeboden, die elk 1100 doelgerichte bewegingen omvatten.

Deze manipulatie volstond om effectief een leereffect uit te lokken: de participanten maakten in latere blokken gemiddeld snellere bewegingen dan in eerdere blokken, terwijl de accuratesse stabiel bleef. Eenzelfde leereffect werd geobserveerd in de sterkte van de 1/*f* schaalverhouding. Na veelvuldige oefening vertoonden de participanten een duidelijker 1/*f* patroon in de tijdseries van de 1100 bewegingstijden. Dit resultaat bevestigde de voorspelling dat de sterkte van het 1/*f* patroon een betrouwbare indicator is voor motorische vaardigheid.

In een vervolgstudie (**zie Hoofdstuk 3**) werd eveneens gebruik gemaakt een Fitts taak, maar ditmaal moest er slecht één blok van 1100 bewegingen afgelegd worden, met de voorkeurshand. Er waren twee taakcondities, één met een erg hoge moeilijkheidsindex, en één met een erg lage moeilijkheidsindex. In de moeilijke taakconditie vond de speed-accuracy trade-off plaats, waar de Fitts taak zo berucht om is: snellere participanten voerden de taak minder accuraat uit, en tragere participanten voerden de taak accurater uit, ondanks dat alle participanten geïntrueerd werden om de taak zo snel en zo accuraat mogelijk uit te voeren. Opmerkelijk was dat de snellere participanten ook een duidelijkere 1/*f* structuur vertoonden in de duratie van de bewegingen, maar een meer willekeurige structuur in de amplitudes van de (minder accurate) bewegingen. Meer accurate participanten vertoonden dan weer een duidelijkere 1/*f* structuur in de bewegingsamplitudes, maar een meer willekeurige structuur in de (tragere) bewegingsduraties. Hiermee werd een trade-off tussen spatiële en temporele 1/*f* stromen aangetoond die contingent is op de zo bekende speed-accuracy trade-off.

Een derde studie (**zie Hoofdstuk 4**) gooide het over een andere boeg en richtte zich op een simpele leestaak bij jonge, al dan niet dyslectische lezers. De taak was om zo snel en accuraat mogelijk hardop woordjes op te lezen, die één voor één op een scherm verschenen. Het was niet verwonderlijk dat de dyslectische lezers de taak minder snel en accuraat uitvoerden dan de gemiddelde lezers. Opmerkelijker was dat de gemiddelde lezers een veel duidelijkere 1/*f* structuur vertoonden in de tijdserie van reactietijden vergeleken met de dyslectische lezers. Ook bleek de ernst van de leesstoornis sterk te correleren met de mate van 1/*f* ruis in de

reactietijdreeksen: een ernstigere leesstoornis hangt samen met een meer willekeurige temporele structuur in de reactietijden, een minder ernstige leesstoornis hangt samen met een duidelijker 1/*f* patroon.

Een vierde studie (**zie Hoofdstuk 5**) richt zich op een methodologisch probleem bij het toepassen van een van de vaak gebruikt analysemethoden (m.n. spectraal analyse) om de sterkte van een 1/*f* schaalverhouding te bepalen. Het probleem doet zich enkel voor bij het analyseren van continue processen, maar niet bij het analyseren van discrete processen, zoals bijvoorbeeld reactietijden. Continue processen worden gemeten met een vooraf bepaalde sample frequentie. Als een dataserie lange-termijn afhankelijk is, treedt er een vreemd effect op. Als met het process sneller gaat samplen, is de dichtheid tussen de opeenvolgende datapunten niet enkel kleiner, de hoogste frequenties in het signaal hebben ook een lagere amplitude vergeleken met een process dat trager gemeten wordt. Dit vormt een artifact in spectraal analyse, dat in deze studie aan hand van empirische en gesimuleerde datareeksen wordt aangetoond, en waarvoor een eenvoudige oplossing wordt voorgesteld.

In de tweede sectie van **Hoofdstuk 5** worden er enkele testbare hypothesen toegelicht voor de claim dat 1/*f* ruis duidt op complexiteit in het bestudeerde systeem. Deze hypothesen worden besproken aan hand van een aantal cognitieve studies die zich richtten op manipulaties van 1/*f* schaalverhoudingen. In een volgende sectie van hetzelfde hoofdstuk licht Didier Delignières zijn visie toe over het phenomeen van 1/*f* schaalverhoudingen in motorische dynamiek, en in een laatste sectie worden de verschillen en overeenkomsten tussen deze verschillende visies besproken.

Het laatste hoofdstuk van dit proefschrift (**Algemene Discussie**) had als doel de globaliteit van de relatie tussen 1/*f* schaalverhoudingen en coordinatie in het bestudeerde systeem te belichten. De empirische studies in dit proefschrift passen in een ruim, multidisciplinair kader dat zich over een groot aantal niveaus van analyse uitstrekt, van het niveau van de cel, de activiteit van het centrale zenuwstelsel, andere lichamelijke en fysiologische processen, tot het motorische en cognitieve niveau. Verder heeft deze discussie aandacht voor de verschillende pertinente theorieën over 1/*f* schaalverhoudingen in menselijk gedrag. Elk van deze theorieën wordt dan ook besproken in het licht van de algemene associatie tussen systeem coordinatie en 1/*f* ruis.

Publication List

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Wijnants, M. L., Bosman, A. M. T., & Van Orden G. (2010, March). *Reading fluency is in the dynamics: A self-organization perspective on cognition.* Paper presented at the 4th International Nonlinear Science Conference, Palermo, Sicily.

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Curriculum Vitae

Maarten Wijnants werd geboren op 23 mei 1985 in Bonheiden, België. Na het afronden van zijn secundaire studie in de richting Menswetenschappen aan het Virga-Jesse college te Hasselt (België), volgde hij de bacheloropleiding cognitieve psychologie aan de Universiteit Maastricht, waar hij in 2007 ook zijn Master of Science behaalde in de afstudeerrichting Applied Cognitive Psychology: Work and Organisational Psychology. Zijn afstudeeronderzoek richtte zich op veranderingen in fractale dynamica in motorisch-cognitieve leerprocessen, en werd uitgevoerd aan de Radboud Universiteit te Nijmegen onder supervisie van prof. dr. Anna M.T. Bosman. Als onderdeel hiervan woonde Maarten het Advanced Training Institute: Nonlinear Methods for Psychological Science bij, georganiseerd door de American Psychological Association, door prof. dr. Guy Van Orden. Na het afronden van zijn masterscriptie, ging Maarten gedurende een jaar aan de slag aan het CAP-center for Cognition, Action, & Perception (University of Cincinnati, Ohio) als onderzoeksmedewerker, onder leiding van prof. Van Orden, met als doel zijn onderzoek naar schaalverhoudingen in cognitieve processen voort te zetten. Van eind 2008 tot midden 2010 was Maarten als docent werkzaam aan de Radboud Universiteit te Nijmegen binnen het bacheloronderwijs van het onderwijsinstituut Pedagogische Wetenschappen en Onderwijskunde. Hij was betrokken bij 1^{e} jaars cursus academische vaardigheden aan 1e jaarstudenten en bij 3^{e} jaars cursus onderzoeksvaardigheden. In het jaar 2011 kreeg hij een parttime aanstelling binnen het Behavioural Science Institute te Nijmegen, waarin hij zijn dissertatie afrondde.